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Digital Transformation in Maritime and City Logistics

Smart Solutions for Logistics

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Prof. Dr. Dr. h. c. Wolfgang Kersten
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(Editors)

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Preface

Digitalization trends continuous to shape the industrial world opening up new opportunities across a wide range of sectors. Artificial intelligence (AI) is considered a key driver of digital transformation that has the potential to introduce new sources of growth. The recent advances in machine learning and automation have created a whole new business ecosystem.

This year's edition of the HICL proceedings complements the last year's volume: Logistics 4.0 and Sustainable Supply Chain Management. Companies are challenged to reengineer their supply chains to tackle logistics and sustainability issues that exist in such a complex environment, especially with the increased pollution and congestion in cities.

This book focuses on core topics of digital transformation in logistics. It contains manuscripts by international authors providing comprehensive insights into topics such as digitalized and autonomous transport, cyber security, sustainable city logistics or business analytics and provide future research opportunities in the fields of maritime, port and city logistics.

We would like to thank the authors for their excellent contributions, which advance the logistics research process. Without their support and hard work, the creation of this volume would not have been possible.

Hamburg, September 2019

Prof. Dr-Ing. Carlos Jahn

Prof. Dr. Dr. h. c. Wolfgang Kersten

Prof. Dr. Christian M. Ringle

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I.
Maritime Logistics

Automatic Identification System (AIS) data based Ship-Supply Forecasting

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Purpose: The bulk cargo shipping industry is characterized by high cost pressure. Chartering vessels at low prices is important to increase the margin of transporting cargo. This paper proposes a three-step, AI-based methodology to support this by forecasting the number of available ships in a region at a certain time.

Methodology: Resulting from discussions with experts, this work proposes a three-step process to forecast ship numbers. It implements, compares and evaluates different AI approaches for each step based on sample AIS data: Markov decision process, extreme gradient boosting, artificial neural network and support vector machine.

Findings: Forecasting ship numbers is done in three steps: Predicting the (1) next unknown destination, (2) estimated time of arrival and (3) anchor time for each ship. The proposed prediction approach utilizes Markov decision processes for step (1) and extreme gradient boosting for step (2) and (3).

Originality: The paper proposes a novel method to forecast the number of ships in a certain region. It predicts the anchor time of each ship with an MAE of 5 days and therefore gives a good estimation, i.e. the results of this method can support ship operators in their decision-making.

Keywords: AIS data, Ship-supply Forecasting, Dry Bulk Cargo, Artificial Intelligence

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1 Introduction

Maritime transport is by far the most used mode to transport goods worldwide. It is believed that more than 90% of the world's goods are transported by sea (Grote, et al., 2016). Indeed, the seaborne trade has grown by 4 percent in 2017 and 10.7 billion tons have been transported. Especially containerized and dry bulk cargo shipping is growing with the latter one constituting almost half of the total dry cargo shipments (United Nations Conference on Trade and Development (UNCTAD, 2018). Dry bulk cargo is solid raw material which is transported mostly unprocessed and in unpackaged large quantities. It can be easily stowed in a single hold with little risk of cargo damage. Moreover, transporting commodities in bulk provides economies of scale. Most of transported dry bulk cargo is comprised of iron ore, coal and grain but also goods such as agricultural products, cement or forest and steel products are transported in bulk (Rodrigue and Browne, 2002). Ship operators charter available ships to serve as carriers and transport dry bulk cargo from A to B. In the last years, there is a decrease in the world fleet growth each year. However, the supply of vessels still increases faster and is by far greater than the demand. This situation of unbalanced demand and supply puts pressure on freight rates leading to continuously decreasing earnings for ship operators (UNCTAD, 2017; 2018). Because of this situation, it is more important for ship operators to know the future demand and supply as precisely as possible. Especially knowing areas, where many vessels will be available for booking in a certain period, helps to secure cargo to be transported from that area early and then hire ships for a rate, which is cheap due to a high number of competitors. Despite the advantage that can be generated by knowing the number of ships in a certain region, there is a lack of research aiming at ship-supply forecasting. Hence, this paper aims at proposing a way to support ship owners by providing information regarding the expected number of ships in a region at a certain time. The remaining paper is structured as follows: Section 2 introduces general knowledge about forecasting in the maritime industry, automatic identification system (AIS) data as well as reasons for utilizing artificial intelligence (AI) based forecasting approaches. The developed ship-supply forecasting methodology is presented in section 3 and followed by a discussion. Section 4 subsumes the paper by highlighting the main results, discussing important limitations and providing an outlook on future research possibilities.

2 AIS data based forecasting in the maritime industry

Forecasting in the maritime industry plays a central role for all included parties such as harbors, manufacturers, and ocean carrier companies. Without short and long-term forecasting of e.g. demand, the allocation of resources, capacity planning and making investment decisions in case of potentially required upscaling, are nearly impossible (Mensah and Anim, 2016). Hyndman and Athanasopoulos (2018) define five generic steps that have to be processed in order to perform forecasting: (1) Problem definition, (2) Gathering information, (3) Preliminary exploratory analysis, (4) Choosing and fitting models and (5) Evaluating a forecast model. While the step of the problem definition might seem trivial at first sight, it is possibly the most difficult step in the forecasting process as it requires a thorough and deep understanding of how the forecast will be used, what the requirements are and how it fits within the structure and processes of the organization (Hyndman and Athanasopoulos, 2018).

In order to forecast something, information such as statistical data, accumulated expertise of employees or historical data is needed. While historical internal data like actual demand occurrence can be gathered automatically over time, external quantitative data has to be acquired and qualitative data has to be accumulated in some way. Independently from the type of available data, information should be thoroughly analyzed before selecting a forecasting method. This is necessary because various models differ in their applicability. Also the selected model should be able to capture the genuine patterns that can be found in historical data but should not replicate occurrences that happened in the past but are not likely to happen again (Hyndman and Athanasopoulos, 2018). AIS data is one information source, which can be of high value for forecasting in the maritime industry. This data is transmitted by AIS transceivers which are installed on vessels and which automatically broadcast information, such as their position, speed, and navigational status. This information is received by other ships, terrestrial receiver stations e.g. by coastal authorities and by satellites (also referred to as S-AIS). As all ships over 299 gross tons (GT) are obliged to be equipped with such a transceiver since December 2004, the major amount of ships interesting to bulk dry cargo shippers carry one on board (Zorbas, et al., 2015).

The information transmitted is threefold: The (1) dynamic broadcast information contains navigational information, which is updated and transmitted automatically every 2 to 10 seconds. The (2) Voyage related information such as the declared destination and estimated time of arrival (ETA) of a trip and (3) static vessel information containing e.g. the ship identifier, name and type, are entered by the vessel's crew and transmitted every 6 minutes, regardless of the vessel's movement status. As regulations require a substantial portion of ships to transmit AIS data, the amount of data collected over time offers significant analytic potential. Besides fleet and cargo tracking, AIS data is mainly used for maritime security, collision avoidance, fishing monitoring as well as for search and rescue (Weintrit and Neumann, 2013).

Mao, et al. (2018) do not directly focus on using AIS data for forecasting but present the construction of an AIS-based database that can serve as an input for further analyses based on AIS data. By classifying vessels and focusing on AIS data sent by fishing vessels, Mazzarella, et al. (2014) are able to automatically detect fishing areas. Pallotta, Vespe and Bryan (2013) aim at increasing situational awareness in the maritime industry by better understanding maritime traffic patterns. They use an unsupervised and incremental learning approach that derives characteristics of ports and off shore platforms as well as spatial and temporal distribution of routes from AIS data. Their results can form a basis to allow for anomaly detection, i.e. ships that deviate from the identified route patterns. Similarly, Nguyen, et al. (2018) develop a multi-task deep learning framework for vessel monitoring in order to reconstruct taken routes, identify vessel types and detect abnormal vessel behaviors. Anomaly detection is also one of the activities related to how AIS data is used for knowledge discovery in the maritime domain discovered by Alessandrini, et al. (2016). Their survey of recent Joint Research Centre (JRC) activities also identifies the mapping of maritime routes or fishing activities as well as monitoring shipping activities in the arctic or falsification of AIS data, i.e. the verification of trustworthiness of

AIS data, as relevant fields. Another application possibility is presented by Ambjörn (2008) who use AIS data to identify which ships have been close to oil in the Baltic or North Sea over a period of time and are therefore likely to be responsible for such an oil spill.

Regarding the forecast of ship-supply so far - to the best of our knowledge - no research has investigated possibilities to predict the number of available ships in a certain region of interest. While there certainly are sources that use AIS data either to estimate the position of one ship in the future or to identify certain route patterns, the achieved results do not give an indication about a general ship availability in the future. For example, Xiao, et al. (2017) use a density-based spatial clustering of applications with noise (DBSCAN) algorithm to extract waterway patterns and predict maritime traffic 5, 30 or 60 minutes ahead - a time horizon which is not long enough to allow for early cargo offer securing. Similarly, the identification of routes typically taken by ships, as e.g. presented by Mazzarella, Arguedas and Vespe (2015), is capable of increasing maritime situational awareness in general but does not provide information dedicated to a specific situation at a certain place and time of interest.

However, what becomes apparent when looking at sources forecasting based on AIS data, is that most of them apply non-traditional forecasting techniques. In this paper, traditional forecasting is mainly seen as quantitative methods and statistical techniques. They objectively predict the demand based on past patterns and relationships. This means, those techniques need historical data for their predictions and are not able to identify systematic changes. It is important to emphasize that the quality of accuracy mainly depends on the target value that is forecasted. Some aspects can be predicted very exact like for instance the sunset times for the next year, whereas other factors are uncertain to forecast. These are for example exchange rates or stock prices. In general, it is difficult for traditional techniques to manage a huge amount of past data in a way to identify the right patterns and relationships of features. Moreover, often not all of the required data of the past years exist or is available. Also, the weak reference of historical data to current activities is a limitation (Bursa, 2008; Byrne, 2012).

As AIS data contains information sent by a huge amount of ships, its size gets too big for such more traditional, statistical forecasting techniques quite fast. Hence, authors tend to rely on more advanced techniques from the field of so-called AI. There is no commonly accepted definition of what AI is or what methods belong to it, but it is generally described as "computational systems that perform tasks commonly viewed as requiring intelligence" (Poole and Mackworth, 2017). AI-based techniques are capable of processing more data and identifying feature-output relations that remain hidden to both a human observer and most statistical techniques. Hence, they seem suitable to be utilized when forecasting something based on AIS data.

3 AIS data based Ship-Supply Forecasting

3.1 Conceptualization of the forecasting process

The objective of this paper is to develop a method that is capable of supporting decision-makers of ship operators by providing better information about the available ship-supply. Based on expert feedback it has been decided to forecast the availability of ships based on regions not specific countries or ports. For deciding on where to operate ships, i.e. where to secure cargo, it is sufficient to know which regions will be crowded. As moving a ship within one region is not very costly, the information on where one ship exactly is, is not relevant to decision makers. Therefore, the world map has been separated into regions as defined by the cooperating industry expert. As the destination port stated in the AIS voyage data is entered by the crew by hand and thus not standardized, a matching procedure has been implemented in order to assign global positioning system (GPS) coordinates to a stated destination port and subsequently a destination region. Destinations are mainly stated in two ways: They can be stated as the port name that can be matched directly or via regular expressions or stated as the UN Code abbreviation for ports. This United Nations (UN) code format consists of five letters, the first two resembling the country the port is located in, and the latter three abbreviating the city/location of the port. Thus, a comprehensive reference table containing over 6000 ports with their respective UN code abbreviation has been utilized.

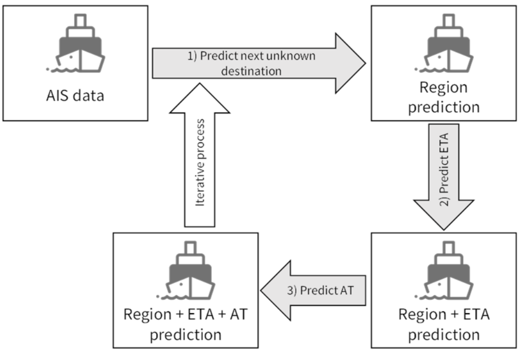

Figure 1: Forecasting process

Forecasting is done on an individual ship level, i.e. it is predicted for each ship at what date it will be at which destination region. To do so, the forecasting process has been divided into several prediction steps as depicted in Figure 1 and described in the following:

(1) Next unknown destination region prediction: The first step is the prediction of the next unknown region. For each ship, it is predicted what the next unknown destination region will be, which the ship will head to after the current destination that is stated in the AIS broadcast. Since the prediction outcome is based on the different 44 regions from the world map, the outcome is categorical. For instance, for ship XY the outcome of the prediction could be region 44.

(2) Estimated time of arrival (ETA) prediction: In the next step, it is necessary to estimate how long it will take each ship to arrive at their destination region. In this case, the prediction outcome is quantitative. For example, ship XY needs 9 days to arrive at the destination region 44.

(3) Anchor time (AT) prediction: In the third step, it is essential to predict for each ship how long it will stay at the destination region until the next trip will begin. Again, the output is quantitative. For instance, ship XY will stay for the next 4 days in the destination region until it will begin a new trip.

After the iterative forecasting process is done, the results for each ship should contain information about the start region and the destination region. Furthermore, the time measures ETA and AT should be included. Additionally, the vessel id should be stated in order to assign each trip to a vessel. Finally, the results are aggregated to provide the relevant information about how many ships are in which region at a certain point of time.

3.2 Selection of suitable forecasting methods

To handle the classification and prediction steps defined in section 3.1 different methods have been compared. Such a comparison is mainly dependent on the available data. The right data preparation is one of the main factors for a high accuracy (Carbonneau, Laframboise and Vahidov, 2008). The case at hand contains prediction and classification problems with an available set of already labeled example data. Therefore, supervised algorithms are the best-fitted ones. Caruana and Niculescu-Mizil (2006) compare supervised learning algorithms using different performance metrics. Their results show that boosted tree algorithms, support vector machines (SVM) and artificial neural networks (ANN) perform best, which is why these three haven been chosen to be tested with the problem of ship-supply forecasting. Based on the data at hand, Markov decision process has also been selected as an alternative method to the machine learning approaches. The reasons for this additional selection is that especially for the region prediction the number of next unknown destinations is limited and Markov decision processes are suitable to depict the situation of selecting an action, i.e. a new region, based on the current state of a ship.

XGBoost is a scalable system implementing the gradient decision tree boosting approach based on Friedman (2001) and is widely used by data scientist, e.g. in machine learning challenges. With XGBoost simple, weak decision tree models are used as a basis. New models are created to predict errors of earlier ones and this way to iteratively improve a final model with marginally modified parameter settings. Its major contributions are among others a sparsity-aware algorithm for parallel tree learning and the ability to handle instance weights in approximate tree learning (Chen and Guestrin, 2016; Reinstein, 2017). SVMs as well as ANNs are quite common supervised machine learning techniques. The first aims at identifying a hyperplane, which best separates the given data points based on their features to then classify new data points according to this hyperplane. The hyperplane forms a boundary separating the data points with the biggest possible distance to them (Hearst, 1998; Russel and Norvig, 2017). ANNs are built after biological networks such as the human brain. The approach is able to detect hidden relationships within the input data. An ANN typically consists of one input layer, several hidden layers and one output layer each consisting of several neurons, which are connected to each other. Each neuron possesses an activation function, which determines whether the neuron is triggered by the former layer's signals, i.e. the input data. The triggered neurons process the data based on their activation function. The connections between each neurons have a certain weight and the learning process is based on placing adjusting these weights depending on the error of the output produced by the neurons (Tu, 1996; Poole and Mackworth, 2017). In contrast to the other compared approaches, a Markov decision process is no machine learning approach. It is a mathematical framework applied for modeling decision making on a stochastic background. It is based on a discrete time stochastic process, consisting of the current state and possible actions that are to be performed in order to get to the next state. Thus, a Markov decision process consists of a set of possible world states and a set of possible actions (Sutton and Barto, 2017).

For each of the selected forecasting methods and each of the forecasting steps, a prototype has been implemented. The available AIS data has been divided into 90% training and 10% test data. Having executed all prototypes, some performance measures have been calculated to compare the

different methods (cf. Table 1) and Based on the results from the testing phase, it has been decided to use a hybrid solution for the final implementation. For the next unknown region prediction, the Markov decision method was used. For the regressions of ETA and AT, XGBoost was applied. Thus, for the final solution these two methods have been combined into one iterative forecasting process. The step-based forecasting allows for selecting the best approach for each step and hence a hybrid solution leads to the overall best results. As e.g. the accuracy of the ETA forecast depends on whether the correct next unknown region has been predicted, the ship-supply forecasting process will naturally lead to better results when selecting the best-fitted approach for each step.
Table 2).
The results show that the Markov decision process is best suited to predict the next unknown destination region achieving a prediction accuracy of 98%. Also, either about 15 ships too much or too less were predicted for each destination region of the testing data. XGBoost achieves the lowest mean absolute error (MAE) for both ETA and AT prediction, while the root mean square error (RMSE) is about the same for all tested approaches. For each trip of the testing data, on average four days too much or too little were predicted for the ETA. For the AT prediction, with XGBoost roughly four to five days too much or too little were predicted.

Table 1: Measures of next unknown region prediction

	Accuracy	F1	MAE	RMSE
Markov	0.974	-	15.81	24.09
XGBoost	0.494	0.472	666.47	1840.03
ANN	0.519	0.29	1445.95	3719.95
SVM	0.502	0.361	832.6	2028.23

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Table 2: Measures of ETA and anchor time prediction

	ETA: MAE	**ETA: RMSE**	**AT: MAE**	**AT: RMSE**
Markov	4.9	14.21	5.8	13.63
XGBoost	3.96	14.7	4.48	14.1
ANN	4.86	14.48	4.89	13.84
SVM	5.45	14.47	5.39	13.74

3.3 Visualization and utilization of forecasting method

The results generated by the hybrid, three-step and AI-based algorithm are presented in a Table to the decision maker (Table 3 shows an example of how such an export looks like). This Table provides the number of ships for each destination region along each day of the forecasting horizon. By this, the decision maker resp. ship operator gets a brief and extensive overview of all ships e.g. for the next 30 days.

Based on this Table the decision-maker can estimate if it is promising to accept a cargo offer in a certain region. For example, there will be comparatively many ships in region 1 around July 23. Hence, it will likely lead to low rates for hiring a ship. If the decision-maker is now able to secure cargo in that region for the respective time, it will most likely generate more earnings than in regions or times with a smaller level of ship-supply.

Table 3: Example Ship-Supply forecast export

Region	**22.07.18**	**23.07.18**	**...**	**20.08.18**
Region 1	7	18	…	1
Region 2	0	0	…	12
Region 3	0	15	…	0
…	…	…	…	…
Region n	3	1	…	0

More sophisticated or graphical visualizations are possible as well for example by using tools such as Kibana, which allow to generate heat maps according to the number of available ships etc. However, expert feedback was given that a simple list with numbers is preferred as it reflects the results more detailed and accurately. Moreover, domain knowledge can be better used to interpret the numbers regarding their validity and significance.

The entire forecasting process was developed in the script language R. It was divided into five different R scripts in order to deploy the entire concept. An overview script, which combines all other scripts, reads all necessary input data, starts the data preparation function and later on, the iterative forecasting process. Lastly, the forecasting results are stored in the target Table of the database. There are three scripts containing the functions necessary for the forecasting process: one for the data preparation, one for the Markov decision models and one for both XGboost models (ETA and AT). The fifth script includes all necessary packages and dependencies and is sources by the overview script to provide them. All that is needed to run and use the forecasting process is a database storing the necessary AIS input data and providing Tables for storing the generated output as well as the presented scripts, which can e.g. be stored on a server to be run from there. The next step could be to integrate a job to start the forecasting process regularly in a time interval as desired. Once the forecasts are calculated, ship operators can use it as an additional source of information to base their decisions on.

4 Conclusion

Overall, the paper proposed a three step, AI-based method to forecast the number of ships in a certain region at a time of interest. The ship-supply forecasting method has been conceptualized on the foundation of available literature as well as expert feedback. Based on predefined maritime regions as well as the estimated time of arrival per ship, it has become possible to forecast ship availability as far as the time horizon of the existing input data allows.

While the objective of the paper has been fulfilled, there are certain limitations, which should be kept in mind, as well as possibilities for future development to enhance the method and its results. First of all, the set of techniques evaluated can be extended. A number of approaches has been sought which are appropriate to the problem as well as the data and are therefore promising, but as the set was not exhaustive, it cannot be guaranteed that no other approach leads to equally good or even better forecasts. Moreover, the time horizon of utilized AIS data has been limited and a test with an extended data set, spanning over a longer time horizon, would surely increase the meaningfulness of the forecasting results. Moreover, it is necessary to always keep the accuracy of the predictions in mind when using them for decision-support. The real number of available ships will differ from the predicted numbers and hence have influence on the rate at which ships can be booked. Nonetheless, a deviation of 4 to 5 days in ETA or AT is not major compared to the days it takes a ship to travel from one region to another. Hence, the difference between expected and actually available ships should not be big enough to not use them as a support for deciding where to secure cargo. Even if the number of ships differs, the rates at which ships can be rented will not change dramatically if the predicted amount is roughly as expected.

Regarding future research possibilities, especially the integration of further information to improve the forecasting quality is of high importance. First, expert knowledge could be integrated e.g. in the form of rules. The main purpose could be to remove errors in the forecasting results. For example, explicit knowledge about ports just serving as maintenance or refueling points could be incorporated this way. Other interesting aspects are region relationships or time specifications. Explicit knowledge about the relationships between regions could be useful to avoid forecasting trips from some region to another that would never happen in reality. Based on these rules, the Markov probability matrix could be adjusted to avoid impractical trips. Additionally, time specifications could contain information such as, how long a vessel needs at least to go from one region to the destination region or what the maximum anchor time of a vessel could be. The new information enables the results to be checked and adjusted in case erroneous predictions and also so the adjustment of the learning model. Another way to improve the forecasting results is to integrate known seasonality patterns. As seasonality is one of the greatest uncertainties in dry bulk cargo shipping and leading to e.g. freight rate volatility, the integration of its patterns can result in a higher prediction accuracy. Aspects that could be used to depict seasonality are commodity seasonality, weather data or general maritime traffic patterns.

Even when keeping the limitations and possible improvements in mind, the proposed method is a good starting point for generating valuable information, which can support ship operators in their daily business and help to generated more revenue.

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[1] https://www.24vision.solutions/

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Integrated Domain Model for Operative Offshore Installation Planning

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Purpose: This article aims to identify common structural elements in the descriptions of both approaches, enabling the application of model transformations.

Methodology: Several models of both types will be compared, combining relevant concepts, i.e., entities, attributes and relationships into a generalized model. In a second step, elements crucial to either type of model are identified. For the remaining elements, interdependencies and redundancies will be identified to enable a model reduction.

Findings: While the structure and notation of both approaches are different, both describe the same fundamental concepts and relationships. The article provides a data model of these common concepts for the operational planning of offshore activities, including weather restrictions and forecasts.

Originality: In current literature, there exist no approaches to combine mathematical optimization with event-discrete simulations in the context of offshore wind farm installations. To harness the advantages of both approaches in an integrated methodology, a model of common concepts is required, which does not exist at this time.

Keywords: Offshore Wind Energy; Operative Installation Planning; Domain Model; Mathematical and Simulation-Based Models

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1 Introduction

Wind energy constitutes one of the most promising technologies to generate large amounts of sustainable energy. In 2017 new wind farms with a capacity of 52 Gigawatts were installed, raising the amount of energy produced by wind energy by approximately 11% to a total of 539 Gigawatts word-wide (REN21, 2018). In this context, offshore wind farms (OWF) are particularly capable of delivering large amounts of energy due to the higher availability of wind and higher wind speeds at sea (Breton and Moe, 2009; Sun, Huang and Wu, 2012). According to (REN21, 2018) an exponential increase in offshore wind energy could be observed over the last decade.

Despite the apparent advantages of OWFs, their installation, operation, and maintenance pose particular challenges compared to onshore wind farms. Generally, offshore wind turbines are higher powered, and their components are larger and heavier than their onshore counterparts, resulting in increased costs, e.g., for founding structures, network connection, and resources, like vessels and storage spaces. Besides, highly dynamic weather conditions at sea render consistent mid- to long-term planning of resources and operations difficult. Generally, about 15% to 20% of the costs for OWFs can be attributed to logistics during the construction process, demonstrating high potentials for optimization (Lange, Rinne and Haasis, 2012; Dewan, Asgarpour and Savenije, 2015; Muhabie, et al., 2018). Current research shows a trend towards more high-powered wind turbines with capacities over 10 or 12 Megawatts, e.g., compare the European research project (European Council, 2018). Such turbines generally require deeper water with depths of 20-50 meters for installation, which are commonly located at distances starting at 30 km to 100 km off the shoreline (Muhabie, et al., 2018), further complicating the planning and execution of operations.

To support decision making during the installation of OWFs, suitable decision support systems are required, which combine capabilities for long-term planning with short-term control. On the one hand, long-term plans can reduce the overall cost efficiently by allocating resources. On the other hand, a decision support system requires short-term control strategies to cope with ever-changing weather conditions and to handle uncertainties involved with weather forecasts. In previous work, we identified several planning tasks, which make up the overall planning problem for the installation of offshore wind farms. These cover different time horizons and activities, which range from the overall long-term capacity planning for vessels and storage, over the production and transport planning of components to the short-term operations planning (Rippel, et al., 2019a). For each of these planning tasks, there exist different approaches in the literature that can be classified in simulation-based approaches and mathematical/optimization based approaches. Each of these classes provides its particular advantages and disadvantages compared to the other, e.g., in terms of speed or solution quality.

This article focusses on the operational planning of offshore operations in the context of the OWF installation planning. To harness the advantages of both model classes, this article aims to identify shared concepts between these classes and to summarize this information into a consolidated domain model. Using this domain model, model transformations can be enabled to convert in between simulation-based and mathematical approaches to evaluate and compare their individual performance. According to (Larman, 2001) a domain model is used to decompose a targeted domain into noteworthy concepts, attributes and associations, thus describing which objects and concepts are important for a given area of focus. Domain models can take different forms and complexities, from simple schemes for databases to complex models, including inheritance and interdependencies (Fowler, 2011). Common choices for domain models are logical modelling languages (e.g. for ontologies) or the Unified Modelling Language, as chosen for this article.

The next section 2 shortly sketches the installation process. Afterward, section 3 summarizes current planning approaches and discusses the advantages and disadvantages of their corresponding classes. Sections 4.1, presents the methodology used to derive the domain model, while sections 4.2 and 4.3 describe its application to mathematical formulation and simulation-based formulations to determine parameters and the class hierarchy. Finally, section 4.4 presents the consolidated domain model for the operational installation planning of OWFs. Finally, the article closes with a description of future work.

2 Process Description

According to (Vis and Ursavas, 2016) and (Quandt, et al., 2017) the installation process comprises three stages: First, the installation of foundations and the connection to the energy grid. Second the installation of top-structures and third, the ramp up and commissioning. Commonly, one service provider is responsible for the installation of foundations and cables, and another provider takes over the installation of top-structures and the commissioning. These service providers usually conduct their own tasks sequentially, i.e., the installation of top-structures generally commences after all foundations are installed and connected. In practice, it is not uncommon, that these stages take place in different years, i.e., in the first year all foundations are installed, in the second year, the remaining stages are conducted. While the components and resources in the first and second stage are different, the overall process remains the same. This results in two, more or less, independent planning problems of the same overall type.

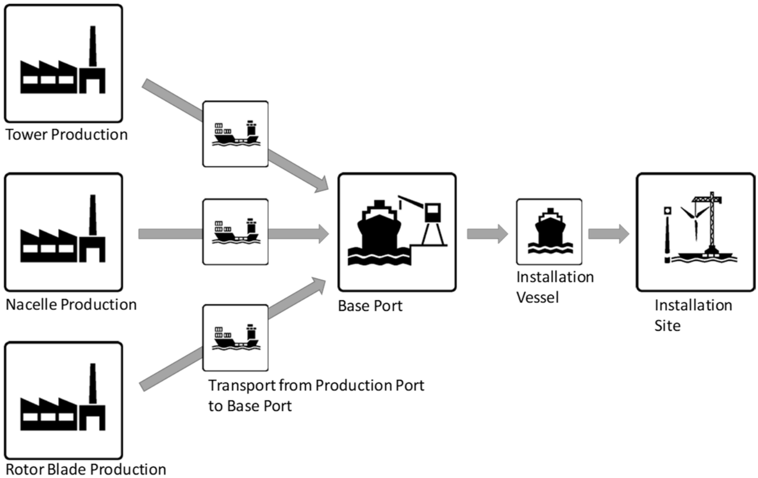

Figure 1: Conventional installation concept (Oelker, et al., 2017)

In literature, there exist two different concepts for the overall installation process. The classic concept, which is also used in this article, is given in-Figure 1. This concept assumes that the components are buffered at a so-called base port before installation. So-called heavy lift vessels (HLV) perform the transport from the production sites to the base port as these vessels usually come at comparably low charter rates. During the construction process, an expensive installation vessel, usually a so-called jack-up vessel, picks up these components from the port, travels to the installation site and performs construction there. In contrast, feeder based concepts try to eliminate expensive travels of the installation vessel from the base port to the installation site by directly feeding components from the manufacturing sites to the installation site (Oelker, et al., 2018), or if necessary, from the base port (base-port feeder concept) (Ait Alla, et al., 2017) to the installation site by specialized heavy lift vessels. For this concept, these HLVs require specific technologies to enable transshipment operations, e.g. to remain steady while loading or unloading components at sea.

The installation of the top-structures is performed sequentially, generally in a single session (Rippel, et al., 2019b): Therefore, the installation vessel first positions itself close to the foundation and begins its jack-up procedure. Afterward, the components are assembled from bottom to top as tower, nacelle, blades and finally the connecting hub. Once the installation is completed, the vessel jacks-down again and moves to the next installation site or back to the base port. After the jack-up has been finished, installation vessels usually remain stationary until they finished the installation. In practice, a single position should only be used once for jacking-up to avoid damaging the foundations or even the installation vessel itself, as the seabed is punctured, sometimes for several meters, during jack-up. Each of the listed offshore operations requires specific weather conditions to be performed, which are usually given by maximum wind speed and maximum wave height. If these requirements are not met for the entire duration of an operation, the operation cannot be started or has to be aborted and re-started later on, resulting in expensive waiting times for the installation vessel. As a result, dynamic weather conditions at sea can result in high, unplanned costs. Moreover, charter contracts often set different prices for vessels being in port and for being offshore, which can differ by approximately 30% (Rippel, et al., 2019b).

3 Current Planning Approaches

Whereas the overall installation planning comprises several sub-tasks, the operative installation scheduling provides the most important of these tasks. While it is constrained, e.g., by available capacities, optimal capacities cannot be determined without an operative schedule or plan. Consequently, this article focusses on approaches for the operative plan generation.

3.1 Classification of Approaches

Within the literature, only a few articles deal with the operative installation planning explicitly (Vis and Ursavas, 2016). Nevertheless, these approaches can be classified according to their usage, either of mathematical formulations or event-discrete, usually agent-based, approaches. In general, both model classes provide their own advantages (Rippel, et al., 2019a):

Simulation-based models usually have a high level of detail, as they model and simulate the behavior of single entities and their interactions over time. This facilitates the inclusion of time-dependent data, e.g., weather information, which the simulation can sample at every time instance. The most common form of these models found in literature represents discrete-

event or multi-agent simulation models. For plan generation, simulation-based approaches can record the different actors' decisions and events during the simulation run and provide these as a plan afterward. To enable the generation or optimization of plans, a distinct optimization component is required. In general, choices for such optimizers are, e.g., Genetic Algorithms, Tabu-Search or similar metaheuristics. These approaches can be found for various planning tasks in literature and are usually referred to as simulation-based optimizations. For example, (Frazzon, Kück and Freitag, 2018) apply genetic algorithms for manufacturing planning and scheduling. Nevertheless, in the context of the installation planning for offshore wind parks, the literature review shows no applications of simulation-based optimizations as shown further below. All identified simulation approaches in this domain only focus on the simulation of predefined scenarios.
While the high level of detail allows simulation-based approaches to evaluate a scenario thoroughly and enables a high degree of adaptability when it comes to different settings and conditions, the high computational requirements and high complexity in creating and maintaining the model can be considered a disadvantage. These hold especially true if combined with simulation-based optimizations, which usually have to evaluate a large number of scenarios. Moreover, when the overall planning problem becomes larger, e.g., by integrating the capacity planning, the simulation model and the corresponding amount of required experiments grow accordingly. In simulation-based approaches, it can be hard to impossible to split several, interconnected planning tasks into separate models.
Mathematical models usually come tailored to the problem they should solve, resulting in a more focused and reduced formulation. Moreover, most mathematical models found in the context of the offshore wind farm

installation planning represent optimization problems. Models of this class rarely simulate the actors' decisions or events that happen over time but calculate plans or solutions on a more abstract level of detail. If set-up correctly, these models can yield optimal solutions with comparably low computational times for single tasks of the overall planning problem. In contrast to simulation-based approaches, distinct models can solve separate planning tasks, e.g., operations planning, capacity planning, etc., only requiring the corresponding constraints and results of other models. This facilitates the model creation and maintenance as several smaller models can be easier to handle than a single, complex model. Moreover, models can be developed for different tasks on different levels of abstraction, allowing for a more detailed selection of tasks to include in the current evaluation.

While the variable level of abstraction provides significant advantages, the inclusion of dynamic, time-dependent effects constitutes a major challenge. Higher levels of abstraction also require more abstract representations of such effects, which can result in unreliable results or prevent certain degrees of abstraction altogether.

3.2 Literature Review

In current literature, no work applies simulation-based optimization using discrete-event or multi-agent simulations. Nevertheless, there are several approaches, which use this class of models for an evaluation of predefined settings. (Muhabie, et al., 2018) present a discrete-event simulation to compare the effects of dynamic or static assumptions on weather conditions. (Vis and Ursavas, 2016) also apply discrete event simulations to assess the impact of different preassembly strategies on the overall installation process. (Ait Alla, et al., 2017) present a multi-agent based simulation to compare different installation concepts, i.e., the conventional and feeder based concepts. This model is further adapted in (Oelker, et al., 2018) and is also used in this article to determine required concepts and attributes in simulation-based models.

For mathematical models, most of the literature focuses directly on optimization models or on the development of cost models to evaluate different settings against each other. In terms of cost models, (Quandt, et al., 2017) presents a formulation to assess the impact of information sharing between involved companies. (Beinke, Ait Alla and Freitag, 2017) describes a formulation to determine the effects of resource sharing, focusing on sharing heavy lift vessels between different installation projects. (Kerkhove and Vanhoucke, 2017) present a precedence-based formulation of a scheduling problem, focusing on the cost-optimization in commissioning and decommissioning vessels within an installation project. Thus, this formulation presents a mixture of cost model and plan optimization. While most of the following approaches consider either total cost or the overall construction time, they usually rely on less sophisticated formulations for the costing part than the earlier described models. (Irawan, Jones and Ouelhadj, 2017) proposes a time-indexed formulation for the scheduling of offshore operations using a multi-criteria optimization to find the optimal tradeoff between short construction times and minimal overall construction cost. This model was later on extended for the decommissioning of offshore wind farms in (Irawan, Wall and Jones, 2019). (Scholz-Reiter, et al., 2010) propose a combination of a precedence-based job-shop scheduling formulation with a multi-periodic production formulation to optimize operative schedules, later proposing a heuristics-based solution algorithm in (Scholz-Reiter, et al., 2011) for solving larger problem instances. The same model was extended in (Ursavas, 2017) to include probabilistic assumptions about weather conditions. In (Ait Alla, Quandt and Lütjen, 2013) the authors propose a time-indexed job-shop scheduling formulation to determine the number of offshore operations to be conducted within a series of 12-hour timeframes. (Rippel, et al., 2019b) describes a time-indexed scheduling formulation to generate operative plans under varying durations for each operation.

4 Domain Model for the Operative Planning in the Installation of Offshore Wind Farms

This section describes the procedure and results of the domain model deduction. Therefore the next subsection presents the overall applied methodology. Afterwards, the application of selected steps of this methodology is described in more detail. Finally, this section presents the overall domain model.

4.1 Methodology

In general, there exists no standardized procedure to develop domain models. Nevertheless, (Stuckenschmidt, 2011) summarizes some best practices and proposes the following iterative steps to obtain a generalized domain model:

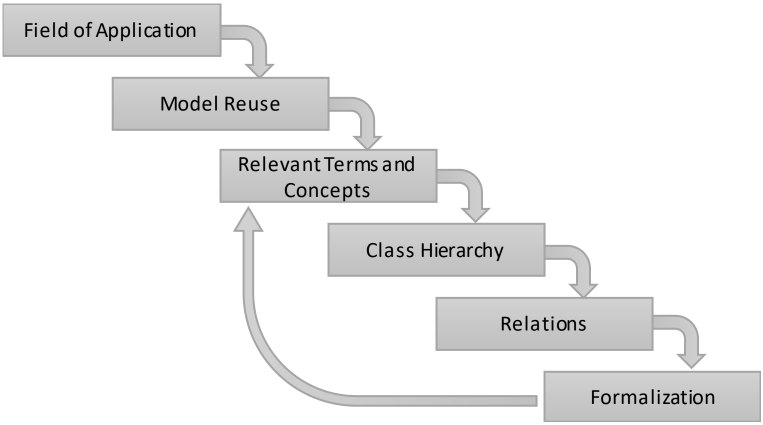

Figure 2: Procedure as proposed by (Stuckenschmidt, 2011)

The first two steps aim to focus the future domain model on the most relevant aspects and to reuse other existing models in the selected domain. Afterward, (Stuckenschmidt, 2011) proposes to follow the next steps iteratively, i.e., to define essential elements of the domain model, integrate them into a class hierarchy, define their relations to other concepts, classes or aspects of the domain model and finally to formalize those elements. During each of these steps, new ideas can arise, e.g., the introduction of more general classes, which requires to refine the overall domain model iteratively.

1. Focus the field of application: The first step in setting up an appropriate domain model, is the definition of the model's focus. The domain model presented in this article focusses on the operative installation planning of offshore wind turbines.

2. Reuse of existing models: The second step aims to identify existing models for this domain which can be used to derive essential concepts and parameters during the subsequent step of this procedure and to simplify the overall domain model design. In the case of the operative offshore installation planning, no other existing domain models could be identified. Nevertheless, several simulations and optimization models have already been described in section 3.2.

3. Identification of relevant terms: The third step of the procedure aims to identify relevant concepts, objects, parameters and relationships within the domain. For example for the operative installation planning such terms are *vessels* and *ports*, but also more abstract concepts like *plans* and *operations*.

4. Definition of a class hierarchy: In a fourth step, the first draft of a hierarchy of the identified terms is setup. Therefore, parameters are assigned to their respective classes. In particular, when working with existing models, this step is used to reorder and aggregate parameters found under different names or notations in different models. Moreover, it is quite common, that different models express the same concept in different ways or use a distinct subtype of the same basic concept.

5. Definition of relations: The next step covers the identification and definition of relationships between these classes. One Example can be the relationship that *vessels* are used in installation *projects* or that *vessels* can perform *operations*. For this purpose, different kind of relationships, e.g., associations, generalization or aggregation, can be used to express relations. Descriptions of common relationship types can be taken from *Unified Modelling Language* (UML), which is often used to describe domain models, or from the *Web Ontology Language* (OWL), which is a logic-based modeling language.

6. Formalization of classes: The final step of the procedure aims at the formalization of the designed domain model. This means that the identified classes and relationships are modeled using a modeling formalism like UML or OWL. Depending on the overall design goal, changes to the class hierarchy or the relationships can be required to satisfy the formal constraints of the selected language. For this article, UML-Class Diagrams were chosen to represent the domain model, as these diagrams are comparably easy to understand while allowing to depict even complex relationships between classes.

To create a common domain model for mathematical and simulation-based formulations for the offshore installation planning, the described procedure was applied in two stages: First, mathematical formulations were used to obtain commonly used parameters. Articles using mathematical formulations tend to describe their model thoroughly, including all relevant parameters and variables. Therefore, they provide a rich source of information on all aspects required for the domain model. During the second stage, simulation-based formulations were used to obtain a clearer picture of superimposed concepts and classes. In contrast to mathematical formulations, articles rarely present a comprehensive description of the underlying simulation model. Consequently, most information regarding simulation-based approaches and their structure can be derived from the parametrizations given. Nevertheless, for this article, we obtained the AnyLogic simulation model used in (Oelker, et al., 2018), which was used as a baseline for the second stage. Additional information was derived, e.g., from (Dewan, Asgarpour and Savenije, 2015), who describe several different settings and scenarios which can be simulated using their tool.

4.2 Definition of Relevant Terms and Concepts from Mathematical Formulations

To identify relevant parameters for the domain model, the mathematical formulations described before were analyzed. Therefore, the parameters and variables were aggregated, consolidating parameters, which have different names or notations in their models. In conclusion, 44 different parameters were identified. Table 1 summarizes these parameters and provides their relative frequency of occurrence. Thereby, a rating of three means that the parameter was present in most, if not all of the models ($\geq$ 70%), while parameters with a rating of one appeared in less than 30% of the models.

Table 1: Aggregated parameters and relative frequency

Parameter	Rel. Freq.	Parameter	Rel. Freq.
Number of Turbines	●●●	Day Rate Active	○○●
Component Type	●●●	Day Rate Waiting	○○●
Comp. Installation Time	●●●	Loading Capacity	○○●
Component Loading Time	●●●	Port Produces Component	○○●
Number of Vessels of Type	○●●	Operation Learning Rate	○○●
Req. Weather to Install	○●●	Number of Jobs	○○●
Seq. of Weather Classes	○●●	Distance between OWT	○○●
Num. of Planning Periods	○●●	State of Turbine in OWF	○○●
Planning Period Length	○●●	Fixed Project Cost	○○●
Traveling Time to OWF	○●●	Energy Per Turbine	○○●
Vessel Type	○●●	Process Chain	○○●
Vessel Loading Scenarios	○●●	Setup Time (Load. Scenario)	○○●
Required Weather to Load	○●●	Setup Cost (Load. Scenario)	○○●
Timeseries of Weather Data	○●●	Seafastening Time	○○●
Project Start Date	○●●	Transshipment Time	○○●
Distance to OWF	○●●	Jack-up Rate (Time)	○○●
Travel Speed	○●●	Minimum Renting Period	○○●
Port Storage Capacity	○●●	Commissioning Cost	○○●
Req. Weather Seafasten	○○●	Decommissioning Cost	○○●
Req. Weather Transship	○○●	Port Process Times (Load)	○○●
Cost for Vessel in Period	○○●	Port Weather Rest. (Load)	○○●

4.3 Class Hierarchy from Simulation-Based Models

Comparing the already acquired parameters with the simulation model from (Oelker, et al., 2018) and parametrizations given in the literature for other simulation models shows complete coverage of all used parameters by the domain model from section 4.2. Nevertheless, as simulation models usually focus on the elements they simulate, these models provide comprehensive information on the overall structure of classes and relationships. An analysis of the simulation model used in (Oelker, et al., 2018) shows, that agents mostly comprise vessels (Installation Vessels, Heavy-Lift Vessels) or locations (Base Port, Production Port, and Wind Farm). Several additional classes are used to capture additional logic and behavior but directly relate to the stated elements. Based on information about the class hierarchy derived from simulation-based models and information about parameters taken from mathematical formulations, the domain model was created.

4.4 Generalized Domain Model

Figure 3 shows all data types, i.e. enumerations, used in this domain model. These constitute lists of different types of objects in the domain. For example, the enumeration *Components* lists all Components relevant for the operative installation scheduling found in literature. Throughout all class diagrams, alternative formulations are given in brackets. For example, some models refer to *Piles* and *Cables*, while other models subsume these as *Foundations*.

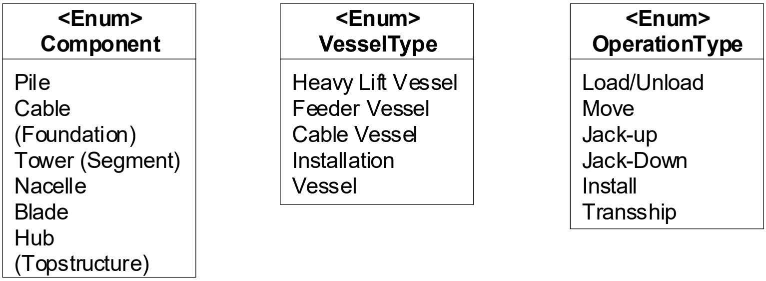

Figure 3: Relevant Datatypes, i.e. lists of operations, vessels and components

Figure 4 shows a general, conceptual overview of the domain model including all classes, subclasses, and enumerations but without parameters. All diagrams given in this section follow the notation of UML-Class Diagrams. The latter are given in subsequent, more detailed Figures later on in this section. The main components covered by this domain model are as given below:

Project: The Project constitutes the main class, linking all other information together. Therefore, it is associated with the relevant ports and the installation site, the available vessels and with the available weather (forecast) data and the schedule.

Location: Locations are used to describe physical locations relevant to the project. These are in particular installation sites, production and base ports.

Vessel and VesselType: Vessels are used to conduct offshore operations. Each vessel is assigned a loading type, which can either be capacitated or follow a fixed loading layout for specific components or tasks. The VesselType serves as a list of different kinds of vessels, e.g., Jack-up vessels or heavy lift vessels.

Component: Components themselves do not provide additional information but are only included as a list of possible components, e.g., blades or tower (segments).

Operation and OperationType: Operations subsume relevant information depending on their OperationType. They are performed by vessels or at ports.

Operative Schedule: As already described in the state of the art, schedules come in different forms depending on their formulation. Most prominent in literature are time-indexed and sequential (precedence-based) schedules. Nevertheless, more coarse, aggregated schedules can also be found.

Weather Data: Weather data is required for the overall planning. In literature, this data is usually taken from records or classified first.

Staff: Staff is required to carry out operations. In contrast, only a limited set of qualified staff is available within a project.

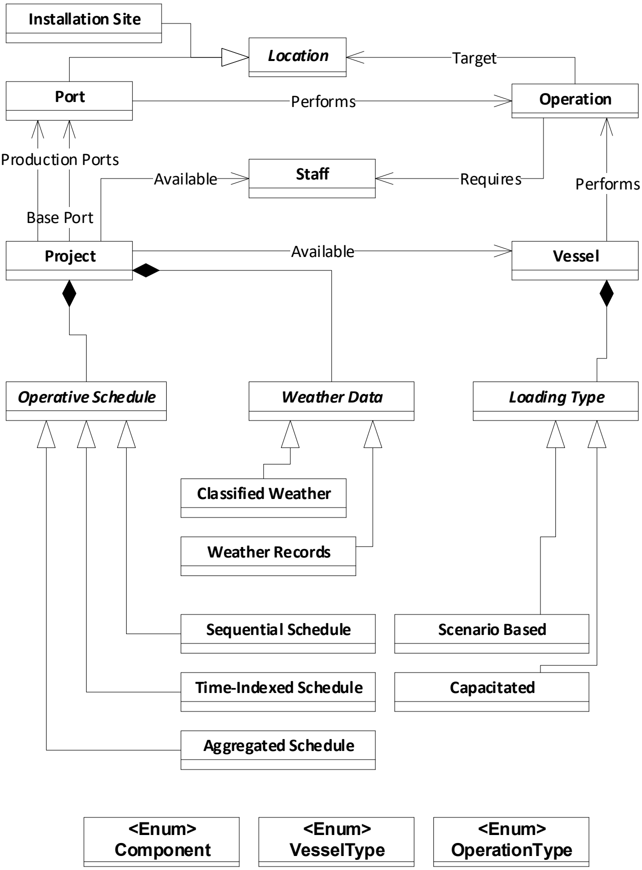

Figure 4: Conceptual overview of the domain model as UML-Class Diagram without attributes

Figure 5 provides a more detailed depiction of these main classes, leaving out further sub-classes. For the attributes, the following diagrams use a simplified notation. On the one hand, all attributes are marked *public* to avoid the need to include methods to obtain and change their values. On the other hand, these diagrams use very basic datatypes, e.g., *Number* or *DateTime*, as they are commonly used in the development of databases. This was done to keep the model more straightforward and easier to understand. Additionally, specific datatype depends on the formulation used as well as on the programming language. Therefore, the presented domain model can be adapted easily to particular requirements without losing out on its degree of detail.

As can be seen in Figure 5, the majority of attributes can be classified in either logistic/technical attributes or as attributes focusing on cost calculations. In particular, for vessels, the majority of attributes aim at capturing the cost of using or applying the vessels. This is due to the nature of the overall problem: operations scheduling. Vessels and other resources constitute the primary, variable cost factor in these projects. Components have to be bought/manufactured anyways, but an efficient use of resources, especially considering the dynamics of weather effects on operational times, is the main focus of basically all optimization/simulation models in this field. Consequently, the majority of parameters aims at processing times, cost rates, or describe parameters which can be used to calculate the previous ones, e.g., distances and speeds. The same can already be concluded from Table 1. The number of turbines to build, as well as the components' installation and loading times, can be found in every model investigated for this article.

Another important set of attributes focusses on the inclusion of weather dynamics. Whereas different models treat weather restrictions differently, e.g., by preventing operations from commencing or by prolonging their duration, the influence of wheatear conditions differentiates this scheduling problem from most other planning problems. Therefore, operations always refer to their corresponding restrictions.

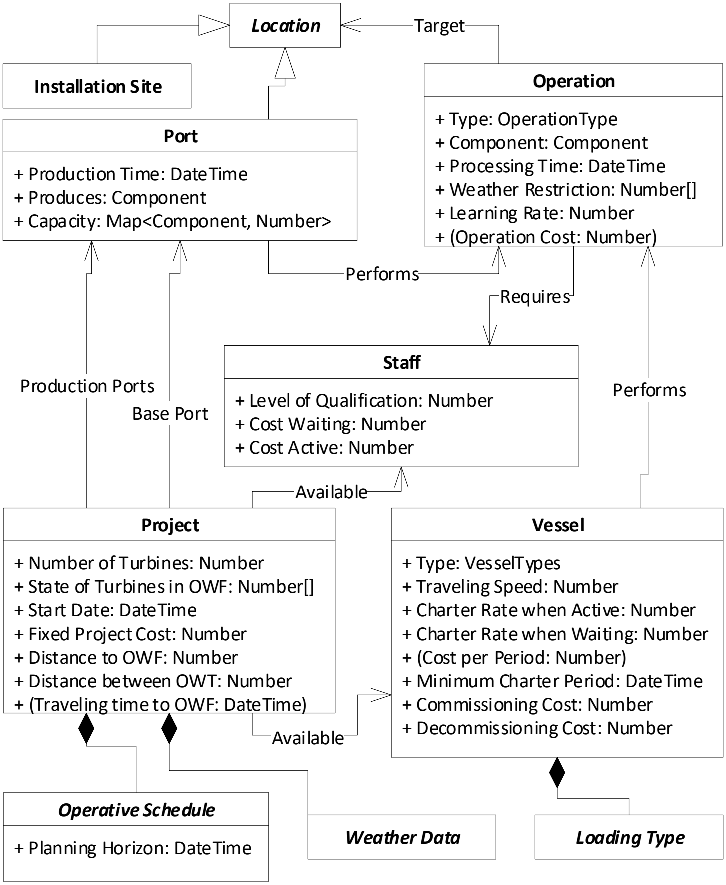

Figure 5: Detailed depiction of the models main entities as UML-Class Diagram

Another set of identified attributes focusses on the representation of capacities. Thereby, storage capacities of locations and vessels are often constrained, either directly by space/weight, by amounts of components, or by the application of loading scenarios. Loading scenarios generally describe predefined sets of components which can be stored or transported together, often including specific frames and layouts, as shown in Figure 5Figure and Figure 7. In models where loading scenarios are used, these are usually connected to set up times and costs for removing or applying these frames. An example of such a loading frame for turbine blades can be seen in Figure 6.

Figure 6: Transport frame for turbine blades on a heavy-lift vessel (Image: Senvion)

Another difference in identified models refers to the way weather data is included. Some models refer to records of weather data, working on, e.g., hourly measurements of actual values for wind speeds and wave heights directly. Other models use abstractions of these data. Therefore, literal classes of weather, e.g., good – moderate – bad, are formed, and sequences of these classes are defined, usually by providing their start dates.
The final core difference between models concerns the plan they generate by optimization or use for their simulation. The most common sub-types are time-indexed or sequential schedules. Some authors also use aggregate plans, which do not schedule operations directly but usually provide the number of operations to be performed during a period. Whereas the overall goal of all plans is the same, i.e., to provide a feasible and efficient sequence of operations, the formulation of these plans and thus, the used attributes can differ strongly, as shown in Figure 7.

5 Conclusion and Future Work

This article presents a domain model for the operative scheduling during the overall installation planning for offshore wind turbines. This domain model aims to consolidate information which is used during the scheduling from different sources. Therefore, relevant parameters were identified based on a literature review of mathematical formulations for the offshore operations scheduling. In a second step, information on existing simulation models was used to refine these attributes into a class hierarchy by identifying related objects and concepts.

The domain model covers the essential classes, e.g., locations, vessels, operations, and components. Nevertheless, future work will focus on the extension of the presented domain model, e.g., by additional resources like cranes, storage capacity and loading docks. These constitute additional cost factors, which have to be regarded but are not covered by concurrent models.

Furthermore, future work will aim to develop model transformations to generate or at least parametrize optimization or simulation models out of the presented domain model. The aim is to enable a concurrent use of both modeling techniques and establish interoperability between models of different resolutions, e.g., aggregate/sequential schedules, and scopes, e.g., capacity planning and scheduling.

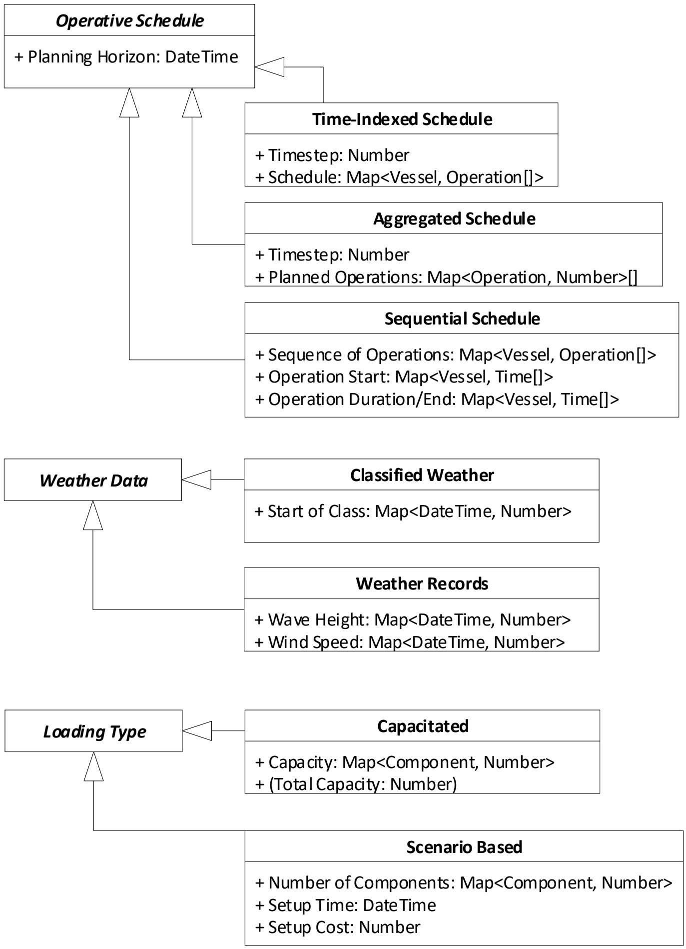

Figure 7: Detailed depiction of the models subclasses as UML-Class Diagram

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Optimization of Maintenance Operations for Offshore Wind Farms

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Purpose: The paper provides insights regarding the optimal maintenance strategies for offshore wind farms. The maintenance strategies distinct from each other with location of the operation base and manner of logistics regarding the vessels.

Methodology: The methodology for modelling the transport for maintenance operations for offshore wind farms is done with a discrete event simulation with data regarding offshore maintenance operations provided from a large-scale research.

Findings: The paper conclude with the optimal maintenance strategy based on the optimal location of the operation base in combination with the best manner of logistics to achieve the preferred requirements with the least transportation costs within the boundaries and limitations of this research.

Originality: There are no current papers regarding the maintenance operations for offshore wind farms located far in the Nord Sea.

Keywords: Offshore Wind Farms, Maintenance Strategies, Optimization, Logistics

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1 Introduction

In this paper multiple maintenance strategies for offshore wind farms are simulated and compared to optimize the total transportation costs, number of required vessels and availability of the wind turbines. This optimization has a positive effect on the price of energy and the emissions during the production of energy. Wind energy is a sustainable and renewable energy source and is becoming a greater part of the worldwide energy distribution. Currently, there are big plans to make new large offshore wind farms deeper located in the ocean. The Dogger Bank is such an example which will hold at least four large wind farms.

Offshore wind farms have advantages and disadvantages in comparison with onshore wind farms. The most important advantages are the availability of space to develop large wind farms without the environmental disadvantages for close population, mainly due to noise and sight issues, and better quality of the wind resources due to the more uniform wind distribution with higher wind speeds (Esteban, et al. 2011). The largest disadvantage is higher installation, maintenance and operation costs. Currently, the Operation and Maintenance (O&M) is estimated to account for 14 % to 30 % of total project life cycle costs of an offshore wind farm. Aspects that an operations team may encounter during the O&M phase are component reliability, accessibility via vessels, transfer of technicians and components to the turbine (Martin, et al., 2016)

Currently, the North Sea contains multiple offshore wind farms from different countries. Most offshore wind farms are relatively close located to the coast. But due to the new EU renewable energy target, there is demand for more wind turbines. As a result, larger offshore wind farms are built further located in the North Sea. These offshore wind farms have more space for a higher amount of wind turbines which is necessary to reach the energy target.

The strategy for closer located offshore wind farms are not compatible for the farther-located offshore wind farms. These new locations cause a difference in the transport and capacity for maintenance operations. Using the strategy for closer located and smaller offshore wind farms will be inefficient for these new farms and research regarding optimizing the transport, logistics and capacity becomes interesting. A strategy with a reduction in the transport costs, man-hours and capacity can have a large impact due to the large scale of the operation caused by the high amount of wind turbines in combination with the long travel distances.

The strategy for large offshore operations is given by Matti Scheu, et al. (2012. The maintenance for offshore wind farms must exceed several conditions before the operation can take place. First, the severity of the maintenance must be declared. The severity specifies the type of vessel which is required. This can be differentiated between a vessel with a crane for heavy weightlifting or without. Second, the personnel must be established. The personnel must be available, meaning enough crew must available that have not been offshore for too long in the previous time. Third, the weather conditions must allow the operation. This means that the current weather must be enough for the operation and will be for the following hours by predictive weather control. The weather condition is met by wind speeds and wave height. If all the above conditions are enough, the operation can take place. If not, the operation is set on hold until all conditions are positive.

2 Methodology

The methodology for modelling the transport for maintenance operation of offshore wind farms is done with a discrete event simulation with data regarding offshore maintenance operations provided from a large-scale research.

First, the characteristics for maintenance for offshore wind farms is analyzed. The data regarding the different maintenance jobs and the characteristics of the vessels are specified by Dinwoodie, et al. (2015). Dinwoodie, et al., describes the correct manner to verify offshore operations with key modelling assumptions. As these data are mean values, these are implemented as an exponential function to show the differentiation.

The transport routes are provided by Marine Traffic which have an intelligent global ship tracking system and therefor accumulates the most accurate and efficient offshore transport routes (MarineTraffic, 2018).

The discrete event simulations are conducted in SIMIO, a software package for visual simulations of logistic systems. The simulation optimizes an ideal situation which does not embeds all affecting conditions as some assumptions are made. The weather and sea conditions are not considered and therefor will not have a negative effect on the maintenance operations. The technician is not simulated and there is no limitation in the amount of technician. However, the maximum technician work shift is 12 hours per day, and this is implemented into the maintenance servers. There is no limitations of size, weight or amount on the vessels, operation bases or wind farms. This research does not implement helicopter usage for the maintenance operations.

3 Situation

The situation of this research is defined by the location of four large wind farms, the required maintenance and the type of vessels. These elements will be discussed in this chapter.

3.1 Dogger bank

The Dogger bank is located in the North Sea and has many favorable attributes which make it an attractive site for offshore wind farm development. The ground conditions are good with relatively shallow water depths. The water depths range from 0 m to 42 m which are suitable for a broad range of foundation construction. The wind resources are good and can reach wind speeds up to 10 m/s. The estimated capacity target of the Dogger bank is 9 Giga Watt (GW) (Forewind, 2010).
Currently, the Dogger bank is in the progress to build four large wind farms, namely Dogger Bank Creyke Beck A & B and Dogger Bank Teesside A & B. Each Creyke Beck wind farm will have a maximum of 300 wind turbines and each Teesside wind farm a maximum of 200 wind turbines (Forewind 2014a) (Forewind, 2014b). According to Marine Traffic, the offshore transport route from Den Helder to the different sites is 175 to 190 nautical miles (Marinetraffic, 2018). A summary of the essential characteristics of the Dogger bank wind farms can be seen in Table 1.

Table 1: Characteristics of the offshore wind farms

	Creyke Beck A	**Creyke Beck B**	**Teesside A**	**Teesside B**
Wind Turbines	300	300	200	200
Large Vessels	3	3	3	3
Small Vessels	13	13	11	11
Crane Vessels	2	2	2	2
Distance to Port [nm]	175	190	190	181

The generated power will be transmitted to land by a variety of phases. First, offshore collector platforms will receive power from the wind turbines via the inter-array cable systems. Transformers will be located on the collector platforms to increase the voltage of the power received from the wind turbine generators so that the electricity can be efficiently transmitted to the offshore converter platform. An offshore converter platform is, therefore, required for each project to convert the power generated by the wind farm from Alternating Current (AC) to Direct Current (DC), for efficient transmission to shore. The offshore ends of the HVDC export cables for each project terminate at one of the four offshore converter platform. Then, the generated power will be transmitted with offshore export tables to onshore converter stations. At this point the generated power will be connected to the onshore power grid (Forewind, 2014a).

3.2 Required Maintenance

According to Carrol, et al., the required maintenance can be specified in different categories which have own failure rate, operation time and required vessels. This model categories the required maintenance in three categories, namely minor failure (1), major failure (2) and major replacement (3). A minor failure occurs most often, takes least time to repair and requires the simplest vessel. Major failures happen less often, require significant longer time to repair and requires a faster vessel to prevent further failures. Major

Table 2: Characteristics of different types of maintenance

	Failure rate [failure/turbine/year]	**Operation time [hours]**	**Type of vessel**
1	6.178	7.5	CTV
2	1.062	26	FSV
3	0.264	52	HLV

replacements occur the least and has the most impact on the maintenance, as a part of the wind turbine requires replacement. The operation time is longer and requires a vessel with heavy lifting equipment. Minor and major failure may require spare parts, but these are always available. The major replacements require larger spare parts which have uncertainty of being available and the capacity must be maintained actively. The summarized specification of these maintenance types is shown in Table 2 provided by Caroll, et al. (2016).

3.3 Type of Vessels

There is a selection of vessels used for maintenance operations which differ in size, speed, capacity and function. The Crew Transfer Vessel (CTV) is the most commonly used way of accessing offshore wind turbines. The CTV's limits the maintenance operations in terms of accessibility and the capacity of technicians and spare parts (Dewan and Asgarpour, 2016). For more complex operations, i.e. major failures, a vessel with more technician and spare parts is required. The Field Support Vessel (FSV) is specified for more technician and heavier spare parts. The Heavy Lifting Vessel (HLV) is specially for large maintenance operation which require new large component, for major replacements. The HLVs are large vessels which contain cranes to lift large spare parts. The specifications of these vessels which are important for the model are shown in Table 3.

Table 3: Specifications of maintenance vessels (Dinwoodie, et al., 2015)

Vessel	**Speed [knots]**	**Maximum Operation time**	**Costs per day [$]**
CTV	20	1 operation	1.750
FSV	12	4 weeks	9.500
HLV	11	Infinite	150.000

The speed specifies the transport time to and from the wind farms. The maximum operation time specifies the ultimate time a vessel must return to shore. This time is limited due to the personnel on board, except for the HLV due to the possibilities on board. The cost per day provides an estimation of the transport costs of the operation.

4 Maintenance

The maintenance is defined by the location of the operation base, the route of the vessels and the strategy which will be applied. These factors will be discussed below.

4.1 Operation Base

The maintenance operation is running from an operation base. The operation base receives the notifications for maintenance, contains the available operation vessels, technician and spare parts. This model differentiates three different operation bases; (1) the onshore base, (2) offshore base and (3) offshore artificial island. The onshore base is in Den Helder and has all vessels, technician and spare parts available. The offshore base is an offshore floating or permanent base which contain technicians, all vessels except HLVs and spare parts required for minor and major failures. The major replacement necessities are unavailable. The offshore island is an artificial island in which all vessels, technician and spare parts are available. Both offshore bases require a restock occasionally to maintain the capacity to avoid downtime of the maintenance.

4.2 Route

The route of the vessels is provided by Marine Traffic (2018). Marine Traffic maintains live updates from offshore vessels and weather conditions. This route is planned with consideration of common routes, shortest path and sea-depth conditions. The route is straight-forward after the coast of the Netherlands is passed.

4.3 Strategies

The general maintenance approach is applicable in all strategies. The strategies are differentiated per location from the operation base and the manner of logistics. The operation base has three possibilities which differ in location and ability of performance: the onshore base at Den Helder is the main port which can handle all kinds of maintenance, contains all vessels and has infinite supply of spare parts. The offshore base is located at the center of gravity of the wind farms and is only capable of minor and major defects, while the major replacements is still run from the onshore base. The offshore artificial island is also at the center of gravity of the wind farms and can run all kind of maintenance jobs. This operation base is only in need of spare parts occasionally which is simulated as another vessel.

The manner of logistics is divided into individual and grouped logistics. Individual logistics have an individual maintenance team to operate the maintenance of each own wind farm and grouped logistics has one maintenance team to maintain maintenance of all wind farms. The summary of the maintenance strategies can be seen in Table 4.

Table 4: Maintenance strategies

Strategy	**Minor failure**	**Major failure**	**Major replacement**	**Logistics**
1	Den Helder	Den Helder	Den Helder	Individual
2	Den Helder	Den Helder	Den Helder	Grouped
3	Offshore base	Offshore base	Den Helder	Individual
4	Offshore base	Offshore base	Den Helder	Grouped
5	Artificial island	Artificial island	Artificial island	Individual
6	Artificial island	Artificial island	Artificial island	Grouped

5 Simulation Model

As stated before, the simulation model is made with the visual simulation program SIMIO. The simulation model differentiates the four offshore wind farms on the Dogger bank with minor failures, major failures and major replacements. Each wind farm is simulated as one entity which accumulates the maintenance demands for the wind turbines present. This results in a higher failure rate per maintenance demand relative to the amount of wind turbines present, which can be seen in Table 5.

Table 5: Yearly failures for each wind farm (Carroll, et al., 2016)

	Creyke Beck A	**Creyke Beck B**	**Teesside A**	**Teesside B**
Wind turbines	300	300	200	200
Minor failures	1.853,4	1.853,4	1.235,6	1.235,6
Major failures	318,6	318,6	212,4	212,4
Major replacements	79,2	79,2	52,8	52,8

As each wind farm is simulated as one entity, the travel distance between the individuals wind turbines is neglected as it takes a relatively small amount of time to travel between the wind turbines. At the beginning of each simulation, the vessels start at the operation base. The wind farms create demand for maintenance based on the failure rate. Each maintenance job relates to a certain vessel, operation time and possible spare parts. The maintenance demand notification enters the operation base which links the notification with the correct vessel and, if necessary, a spare part for major replacements. If the vessel and spare part is available, the maintenance operation starts. The vessel is transferred to the wind farm, operates the required maintenance based on the provided operation time and is transferred back to the operation base.

5.1 Requirements

The requirements describe the minimum performance for the simulation to be met with the chosen strategy and configuration. The requirements must be acquired to get enough power due to the availability of the wind turbines, minimize the transportation costs due to optimization of the usage of the vessels.

The overall performance is calculated with the availability of all wind turbines together. The availability of the wind turbines must be 95 %. Due to the presence of several wind farms and different maintenance performance, the overall performance is not the only requirement. Each sub-element must be optimized to obtain a system which performs enough in all elements. To achieve this, the requirement is set for a minimum availability of the wind turbines of each wind farm to 90 % and a minimum availability of each wind turbines due to each maintenance type to 90 %.

5.2 Experiments

The structure of each strategy is simulated in the model, this means that the operation bases, routes and data regarding the characteristics of the vessels and operation times of the maintenance jobs are set. This provides room for experiments to optimize the number of vessels required to get the objectives per strategy.

The first experiment indicates the maximum number of vessels required for the maintenance. This number of vessels is required to dismiss the waiting time between the maintenance jobs due to the lack of vessels. The second experiment indicates the minimum number of vessels required for the maintenance. This number of vessels obtains the required availability of the wind turbines due to each maintenance type. The third experiment indicates the preferred configurations regarding the availability of the whole. It varies all the combinations of number of vessels and results in the best outcome regarding all the objectives for the least transport costs. The experiments will be replicated ten times over which the average values are taken.

6 Results

First, the results of each strategy are discussed. Secondly, the experiments of each strategy are compared with each other. The best result of each strategy will be chosen for comparison. The best result will be chosen based on the best overall availability up to one decimal in combination with the least transportation costs which is based on the price per day of each vessel.

The last chapters show some interesting extra research results regarding the transport of spare parts and the effect of changing the location of the main port.

Table 6: The results of strategy 1

	CTV	**FSV**	**HLV**	**Up-time**	**Costs**
Maximum	66	36	22	97,0 %	$ 38.3M
Minimum	24	10	4	84,6 %	$ 24,8M
Optimum	38	20	6	95.1 %	$ 32.1M

6.1 Strategy 1

The results from the first strategy can be seen in Table 6. This strategy is run completely from Den Helder with individual logistics. As can be seen in the Table, the configuration of this strategy is optimal with a total of 38 CTVs, 20 FSVs and 6 HLVs. With this configuration all the requirements are met with the lowest transportation costs. The up time of all wind turbines is 95.1 % which will cost roughly 32.1 million dollars for transportation. There is a subdivision of the vessels between the different wind farms. The subdivision is based on the size of the wind farm because the Creyke Beck wind farms have 300 wind turbines and the Teesside wind farms have 200 wind turbines. The division is shown in Table 7 where the Teesside wind farms are indicated as small and the Creyke Beck wind farms as large. Both wind farms occur two times in the Dogger Bank.

Table 7: The subdivision of vessels with strategy 1

	CTV		**FSV**		**HLV**	
	Small	*Large*	*Small*	*Large*	*Small*	*Large*
Maximum	15	18	8	10	4	7
Minimum	5	7	2	3	1	1
Optimum	7	12	4	6	1	2

Table 8: The results of strategy 2

	CTV	FSV	HLV	Up-time	Costs
Maximum	44	21	11	97,1 %	$ 38,2M
Minimum	24	9	2	79,8 %	$ 21,3M
Optimum	27	18	4	95,0 %	$ 34,4M

6.2 Strategy 2

The results of the second strategy, which only differs from the first strategy with the manner of logistics, can be seen in Table 8. The best configuration is with 27 CTVs, 18 FSVs and 4 HLVs. The transportation costs for this configuration is approximately 34.4 million dollars to reach 95.0 % up-time.
A first analysis of the first two strategies shows that individual logistics is preferred over grouped logistics when only the transportation costs are considered. Another interesting fact is that grouped logistics requires less vessels to maintain the up-time over 95 %.

6.3 Strategy 3

The results of the third strategy can be seen in Table 9. This strategy is partly run from the offshore base and the onshore base with individual logistics. The optimized configuration needs 28 CTVs, 10 FSVs and 6 HLVs. This configuration has an overall up-time of 95.2 % which costs 24.2 million dollars for transportation costs.

Table 9: The results of strategy 3

	CTV	**FSV**	**HLV**	**Up-time**	**Costs**
Maximum	46	30	28	97,8 %	$ 38,2M
Minimum	14	6	4	79,8 %	$ 21,3M
Optimum	28	10	6	95,0 %	$ 34,4M

Table 10: The subdivision of vessels with strategy 3

	CTV		**FSV**		**HLV**	
	Small	*Large*	*Small*	*Large*	*Small*	*Large*
Maximum	10	13	6	9	4	10
Minimum	3	4	1	2	1	1
Optimum	5	9	2	3	1	2

Just as strategy 1, this strategy also has a subdivision of the vessels between the small and large wind farms which can be seen in Table 10.

6.4 Strategy 4

The results of the fourth strategy can be seen in Table 11. This strategy is the same as strategy 3 but with grouped logistics. This shows an optimized configuration with 17 CTVs, 8 FSVs and 4 HLVs which costs 28.5 million dollars for the transportation to achieve 95.3 % up-time.

Table 11: The results of strategy 4

	CTV	FSV	HLV	Up-time	Costs
Maximum	31	17	11	97,8 %	$ 33,6M
Minimum	13	6	2	91,1 %	$ 15,2M
Optimum	17	8	4	95,3 %	$ 28,5M

The first analysis based on the outcome of strategy 3 and 4 shows the same results as the analysis of the first two strategies. Individual logistics is preferred over grouped logistics when looked at the transportation costs but requires more vessels.

Table 12: The results of strategy 5

	CTV	FSV	HLV	Up-time	Costs
Maximum	46	30	20	95,7 %	$ 3,6M
Minimum	14	6	4	83,3 %	$ 2,4M
Optimum	16	10	6	95,4 %	$ 3.6M

6.5 Strategy 5

The results of the fifth strategy can be seen in Table 12. This strategy is completely run from the offshore artificial island with individual logistics and needs a total of 16 CTVs, 10 FSVs and 6 HLVs to achieve 95.4 % up-time. This configuration will cost 3.6 million dollars for the transportation.

Just as strategy 1 and 3, this strategy also has a subdivision of the vessels between the small and large wind farms which can be seen in Table 13.

6.6 Strategy 6

The results of the sixth strategy can be seen in Table 14. This strategy is just like the fifth completely operated from the offshore artificial island but with grouped logistics. This will need 21 CTVs, 13 FSVs and 3 HLVs for the optimized configuration. This will achieve 96.4 % up-time with transportation costs of 5.4 million dollars.

Table 13: The subdivision of vessels with strategy 5

	CTV		**FSV**		**HLV**	
	Small	*Large*	*Small*	*Large*	*Small*	*Large*
Maximum	10	13	6	9	4	6
Minimum	3	4	1	2	1	1
Optimum	3	5	2	3	1	2

The analysis between strategy 5 and 6 shows that individual logistics is preferred over grouped logistics based on transportation costs but requires more vessels.

Table 14: The results of strategy 6

	CTV	**FSV**	**HLV**	**Up-time**	**Costs**
Maximum	31	17	10	97,9 %	$ 5.8M
Minimum	13	6	Q	79,4 %	$ 3,0M
Optimum	21	13	3	96,4 %	$ 5,4M

6.7 Results regarding spare parts

Due to the minimal information regarding the spare parts for the major replacements maintenance, the results regarding the capacity management of these parts is shallow. Due to the fact it is unknown which exact type of spare part is required for the maintenance, the spare parts are simulated as one entity. When a major replacement occurs, which requires a spare part, the HLV transports one spare part to the wind farm for the maintenance operation. The amount of required spare parts and the time between them can be seen in Table 15. This data shows the optimum configuration of each strategy which is simulated over the period of a year. An average is taken over this data for further results regarding the spare parts.

Table 15: Restock characteristics of spare parts

Strategy	**Required spare parts per year**	**Time between demand in in hours**
1	235	33,45
2	228	34,47
3	250	31,44
4	266	29,55
5	252	34,47
6	238	33,03

The amount of restocks is related to the number of required spare parts, time between them and the size of the restock vessel. As the size of the restock vessel is unknown, the amount of restocks are set against each other in Table 16. This Table shows the results of the regularity a restock vessel must be transferred to the operation base. This is applicable for the strategies where the operation base is offshore.

Table 16: Characteristics of the restock vessel

Size restock vessel	**Amount of restock per year**	**Time between restock in days**
5	47.0	7.0
10	22.8	14.4
15	16.7	19.7
20	13.3	24.6
25	10.1	32.5

6.8 Results regarding the location of the main port

The main port of this research is Den Helder. This may not be the most optimum location for the main port as the Dogger Bank is in the middle of the North Sea. Due to this reason, the outcome of the best strategy may differ when the location of the main port is changed. For optimal results regarding the effect of changing the location of the main port, the strategy is chosen which operates completely from the main port, which are strategy 1 and 2. The different main ports which are compared are Den Helder and Rotterdam in the Netherlands, Hull and Aberdeen in the United Kingdom, Hamburg in Germany and Esbjerg in Denmark. These ports are terminal ports according to Searates and the marine route between the ports and the Dogger Bank is given by Marine Traffic and the distance can be seen in Table 17.

The data will be compared on the up time of the wind turbines and the associated transportation costs, this can be seen in Table 18. Interesting to see is that main ports which are further away have worse results. This will be further discussed in the conclusion.

Table 17: Distance between Dogger Bank and ports

Port	Distance to Dogger Bank [nm]
Den Helder	174
Rotterdam	195
Hull	128
Aberdeen	196
Hamburg	298
Esbjerg	221

Table 18: Results due to different main ports

Port	Up-time [%]	Transportation costs [$]
Den Helder	95.0	34.4 M
Rotterdam	94.4	36.7 M
Hull	96.4	26.3 M
Aberdeen	94.2	37.9 M
Hamburg	20.4	49.3 M
Esbjerg	87.9	42.5 M

7 Conclusion

Based on this research several conclusions can be drawn regarding the transport for maintenance of large offshore wind farms. The main conclusion to be drawn is regarding the optimal strategy within the boundaries and requirement for this research. Next to the optimal strategy, there can be concluded certain things about the manner of logistics, number of vessels and place of the operation base. The results of the optimal setting of each maintenance strategies can be seen in Figure 1. This graph shows the required number of vessels with their transportation costs to achieve the required availability of the wind farms.

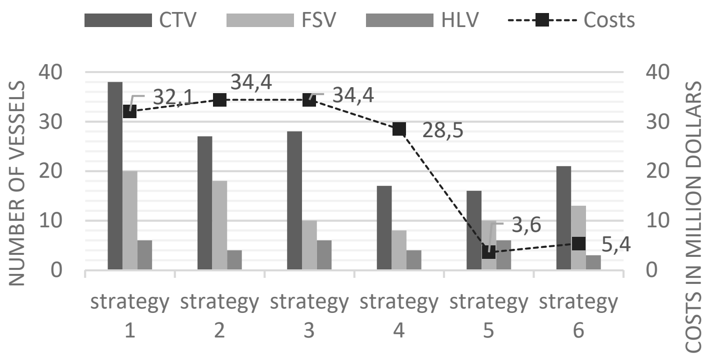

Figure 1: Results of the optimization of each maintenance strategies

The optimal strategy is when the operation base is located at the offshore artificial island, which is in the center of gravity in between the offshore wind farms, in combination with individual logistics, indicated as strategy 5. This strategy requires 3.6 million dollars for the transportation costs to reach up to 95 % up-time of all the wind turbines.

Another conclusion which can be made is based on the location of the operation base. The impact of changing the location of the operation base is enormous regarding the transportation costs. The strategies where the operation base is located onshore requires the most transportation costs as the vessels must transfer the complete offshore route for each maintenance operation. Strategies which operate partly onshore and offshore show less transportation costs but in the same order of magnitude due to the major replacements which are still operated from the onshore base. The major replacements require significant higher transportation costs. The strategy with the complete operation base offshore only requires a fraction, approximately 10 to 15 %, of the transportation costs. Therefore, it is preferred to have the operation base close to the wind farms to reduce the transportation costs.

The manner of logistics also has effect on the transportation costs. The results show that individual logistics is preferred over grouped logistics when only looked at the transportation costs. However, the grouped logistics requires less vessels to maintain the required up-time of all wind turbines but in this research, this is not considered. This conclusion will be further discussed in the discussion and recommendations.

The conclusion regarding the spare parts is that there is approximately daily need for a new spare part. These spare parts must be transferred from the main port to the wind farms. This transfer requires a vessel which can heavy lift these spare parts, such as an HLV. There are also restock vessels which can make the transfer to the offshore operation bases, but this requires more research regarding the size, costs and possibilities of these vessels.

Regarding the location of the main part is an interesting correlation noticeable. As stated, the location of the main port within the strategy where each type of maintenance is operated from onshore to emphasize the difference. The correlation is between the distance between the main port and the Dogger Bank and the performance of the operation. Even up to the point where the overall availability of the wind turbines is down to 20 %. This result stresses the importance of the location of the main port.

8 Discussion

In this section certain discussion points are listed as they possible have certain (negative) effect on the research. These effects can be due to the negligence of certain parameters but also regarding interesting new research topics.
The most important discussion point is regarding the transportation costs. The transportation costs are solely calculated on the length of each maintenance operation. This calculation does not consider other affecting costs such as the investment costs of the vessel, maintenance costs and additional costs when the vessels are not in operation. For example, the reason that grouped logistics are more expensive than individual logistics is that when a vessel arrives at the operation base it immediately has to return back to the wind farm for a new maintenance operation with additional crew and this can cost up to two times the daily price. This differs from the individual logistics because there is a higher change that a vessel will be waiting when maintenance notification arrives and prevents the additional costs. This discussion point will be further elaborated in the recommendations.

As said in the conclusion the location of the operation base has enormous impact. However, during this research it was effortless to change the location of the operation base but, this will bring a lot of issues. For example, the price of the operation bases variate and will have influence on the total transportation costs. If looked at the offshore artificial island, the results show that there will be roughly 30 million dollars available each year for other investments which potentially could cover the cost of such island.
This research differentiates three different types of maintenance and represent all the required maintenance for each wind turbines. During this research this is a good indication of the required maintenance and is enough to distinguish the results between the strategies. However, when a research demands more realistic values regarding the exact outcome of transportation costs, length of maintenance operations and maintenance costs, it is required to differentiate between more types of maintenance and with additional data. In short, this research indicates the differences between different logistic strategies but not exports specific raw data regarding realistic scenarios.

9 Recommendations

The first recommendation is based on the transportation costs. As earlier stated, the transportation costs in this research are not completely investigated. For instance, the transportation costs can include the investment of vessels, the costs of operation bases and the amount of technician. This field of study requires a lot of investigation regarding different kind of elements and further research will result in more realistic values regarding the transportation of maintenance operations.

The second recommendation is regarding the routing of the vessels. This research has a simplistic manner of routing the vessels. In further research, the vessels must involve the maximum duration of the vessel's operation. When this is involved, the vessel can stay at the wind farm for this period and can maintain multiple maintenance operations during one trip. Potentially, this will be positive for the response time of the operation, the number of required vessels and the total transportation costs.

The third recommendation is to investigate regarding the spare parts. The maintenance operation requires spare parts and within this research several assumptions were made but to be confident about the transport of spare parts and the required capacity, further research is required. The research can involve the exact statistics regarding the requirement of the spare parts for the wind turbines but also involve the physical characteristics. These characteristics can provide information regarding the capacity of the vessels, requirements of the lifting equipment. This research will result in more realistic values regarding the costs and capacity of spare parts.

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Modelling of Spare Parts Storage Strategies for Offshore Wind

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Purpose: The production costs of offshore wind energy are currently very high compared to other means of energy production. During the operational phase of an offshore wind park 17% of the operational costs are logistics cost. To reduce the costs, innovative strategies have to be implemented, like improved spare part strategies.

Methodology: In this paper, an agent-based model for the Operation and Maintenance (O&M) supply chain of offshore wind farms is developed analyzing if the storage of spare parts of different offshore wind parts at a central shared warehouse is beneficial.

Findings: Shared storage units for two offshore wind farms serviced from different harbours only yield larger profits for large spare parts transported by a crane vessel. For all other components, rapid access and the resulting higher availability of the wind turbines outweigh the cost savings realized by a central warehouse.

Originality: The developed model is unique as it comprises two storage levels, two wind parks, and different means of transportation for small, medium, and large spare parts on water and land. Until now, no comparable research exists determining the optimal storage level for spare parts in shared storage infrastructure.

Keywords: Offshore Wind, Operation and Maintenance, Agent-Based Simulation, Spare Parts

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1 Introduction

The recent trend for decarbonisation is growing steadily, and the shift from conventional production of energy to renewable production of energy plays an essential role in this transition to cleaner energy production (Kost et al., 2018). Especially offshore wind, with its steady and little fluctuating supply of energy, can play a crucial role in this shift (Reimers and Kaltschmitt, 2014).

The costs of offshore wind energy, however, are currently very high compared to other means of energy generation. Using Levelized Cost of Energy (LCOE), it is possible to compare the costs of different means of energy production by calculating the quotient of average total cost of construction and operation of the power plant over its lifetime divided by the total energy output over the lifetime based on weighted average costs (Astariz, Vazquez and Iglesias, 2015).

For the LCOE of German offshore wind projects, Fraunhofer ISE gives a range from 74,9 to 137,9 EUR/MWh in 2018 (Kost et al., 2018). In comparison, the LCOE of lignite are 45,9 to 79,8 EUR/MWh, of hard coal 62,7 to 98,6 EUR/MWh, of onshore wind 39,9 to 82,3 EUR/MWh and for photovoltaics 37,1 to 115,4 EUR/MWh (Kost et al., 2018). This makes offshore wind the most expensive form of energy production compared to fossil as well as other renewable energy sources. In the long run, the success of offshore wind projects is based on their economic feasibility and thus, a significant reduction in LCOE (Reimers and Kaltschmitt, 2014).

The Operation & Maintenance (O&M) phase is with 20 years the longest and also the only phase during the lifetime of an offshore wind park (OWP) in which revenues are generated. Therefore efficient O&M processes are highly relevant since the availability, and thus the generated power of an offshore wind turbine (OWT) depend on them (Shafiee, 2015). During the O&M phase, logistics costs account for 17% of operational expenditure (Poulsen, Hasager and Jensen, 2017).

Even though the overall number of OWT is globally increasing, the number of manufacturers has declined. Consolidation on the market for OWT has taken place; several smaller companies have merged with Siemens Gamesa which had in 2017 a market share of 44% in Europe where Vestas MHI had 29% (Wind Europe, 2018). Therefore, many OWP share large amounts of spare parts, which allows for the consolidation of spare part inventories to reduce O&M costs.

In this paper, an agent-based model for the O&M supply chain of offshore wind farms is developed to analyse if the storage of spare parts of different offshore wind parts at a central shared warehouse is beneficial compared to the decentral storage at the service harbours of the OWP.

The structure of the paper will be outlined by a literature review of offshore O&M with a particular emphasis on papers for the use of simulation in the O&M phase of offshore wind farms. Then the structure of the agent-based simulation will be developed with an explanation of the input factors leading to the results, and in the last part, the paper will be closed with a discussion of the results.

2 Literature Review

This literature review gives a short overview over the most important literature in the field of O&M of Offshore Wind Turbines (OWT) related to spare parts and inventory management as well as resource sharing and the methods used in this context.

The literature regarding the O&M phase of offshore wind is extensive. Most of these publications are concerned with strategic maintenance decisions like wind farm design, location of service personnel, or outsourcing decisions (Shafiee, 2015). The literature on pooling of resources and spare part management during the O&M phase, however, is very scarce. Three master thesis are looking at inventory policies in combination with maintenance strategies: Dewan (2014) develops a logistics and service model to compare different policies and strategies; Nnadili (2009) focuses floating OWT and Jin et al. (2015) focus on third-party logistics providers. Lindqvist and Ludin (2010) did their Master Thesis about spare part logistics investigating methods for storage and supply of spare parts focusing on stock levels and reorder sizes. Lütjen and Karimi (2012) investigate inventory management during the installation phase. Gallo, Ponta and Cincotti (2012) develop a model which helps to find the right combination of maintenance strategy and warehouse location. Tracht, Westerholt and Schuh (2013) describe an approach for the spare parts management under consideration of the restrictive factors of limited availability of service vessels and changing weather conditions. Rauer, Jahn and Münsterberg (2013) develop a forecasting model to predict the number and type of spare parts required for an Offshore Wind Park (OWP) considering the O&M strategy used.

Rinne (2014) did his dissertation on the topic of spare parts strategies for offshore wind farms during after-sales services. Ferdinand, Monti and Labusch (2018) propose an algorithm to determine the optimized spare part inventory. Zhang et al. (2018) develop an optimization scheme to determine the right update cycle and the number of spare parts necessary. Of all these publications, only the student paper by Lindqvist and Lundin (2010) encompasses the aspect of collaboration by looking at joined warehouses. In the whole literature on the O&M phase of offshore wind, the aspect of resource sharing is only regarded scarcely (Shafiee, 2015). This can be attributed to the infancy of the industry and the competitive nature of the Original Equipment Manufacturers (OEM), there is not much sharing of resources/spare parts done like it is done in other industries.

Most papers which are about sharing or optimizing resource use in the O&M phase are dealing with installation vessels and/or Crew Transfer Vessels (CTVs). Halvorsen-Weare et al. (2017) develop a metaheuristic solution method to do an optimisation for vessel fleets during the O&M phase or Stålhane et al. (2017) who propose a two-stage mathematical model for the optimal use of jack-up vessels for the O&M of offshore wind farms or Stålhane et al. (2016) who use a two-stage stochastic programming model to determine the optimal fleet size for maintenance activities. Schrotenboer et al. (2018) propose the sharing of personnel for the O&M of different offshore wind farms.

The methods applied in the O&M literature are very diverse; most of it based on quantitative modelling using analytical as well as simulation approaches. The most common simulation approach is Monte-Carlo-Simulation (Shafiee, 2015). There are therefore few approaches by authors to use simulation to optimize the O&M logistics, and when done, these authors do not use agent-based models.

Beinke, Ait Alla and Freitag (2017) did a simulation study on sharing of resources during the installation phase. Münsterberg, Jahn and Kersten (2017) as well as, Münsterberg and Jahn (2015) did event-based simulation for the O&M phase of offshore wind farms. Karyotakis (2011) did a model based on Monte-Carlo simulation based on the parameters affecting the O&M phase. Besnard (2013) used a Markov chain model for the O&M processes. Nielsen and Sørensen (2010) wrote a paper about risk-based O&M using Bayesian networks. Dalgic (2015) developed an expenditure model using a Monte-Carlo simulation approach for an optimized fleet of vessels for O&M. Dinwoodie (2014) did a multivariate auto-regressive model in combination with a Markov Chain Monte-Carlo simulation model for O&M. Sahnoun et al. (2015) propose a simulation model using a multi-agent system.

In summary, it can be concluded that no research on spare part strategies considering shared inventory has been done yet. Furthermore, even though the use of simulation is not new to the field, agent-based modelling has to the knowledge of the authors not been applied in the context of O&M of offshore wind logistics.

3 Methodology

In this paper, we develop a model of an Offshore Wind spare parts supply chain for two offshore wind parks using agent-based modelling. Agent-based modelling is a bottom-up methodology which allows a close representation of the of real-world phenomenon like a supply chain with a detailed representation of different actors in the form of agents (Datta and Christopher, 2011; Macal and North, 2014). The behaviour of the overall system is mapped by the interaction of individual agents. An agent is an active unit of the simulation, which is placed in an environment and can make autonomous decisions, underlying a specific set of rules, in order to achieve the goals assigned to it. For this purpose, an agent can perceive the environment and communicate with other agents in it (Wooldridge, 2009). Borshchev and Filippov (2004) compare agent-based modelling (ABM) with the two other most common modelling approaches system dynamics and discrete event modelling. They find that the main difference is the bottom-up approach of ABM. Therefore the resulting system is decentral, and the global system behaviour is the result of the interaction of the different agents. This has some significant advantages. First, it allows the model to be built without knowledge about the interdependencies of the global system. Especially large and complex systems like supply chains can be easier modelled using ABM. Second, ABM is more general and powerful because it enables the representation of more complex structures and behaviours. Third, ABM allows the modelling of very heterogeneous entities like warehouses, trucks, or OWT. Due to these reasons, ABM is well suited to model an offshore wind spare parts supply chain, which is very complex and involves many different actors.

4 Model

The model aims to enable a comparison of two different spare part storage strategies. The first using a shared central warehouse for supplying two OWP, the other one using decentral warehouses at the service harbour of each OWP. Resulting in two storage levels: central and decentral. For this purpose, a model is developed, which includes the most important actors and interactions of a supply chain for offshore wind spare parts for two OWP. The model is developed using the guideline developed by Law (2007) using the software AnyLogic.

4.1 Model derivation

Following standard supply chain frameworks, the model includes material as well as information flow. The material flow is made up of different spare parts. The information flow is opposite to the material flow and includes spare part demands and mission planning. In total, the model (see Figure 1) includes eight different types of agents which will be shortly introduced hereafter.

The structure of the modelled supply chain is based on the best practice for shore based maintenance of OWP (GL Garrad Hassan, 2013). This enables a transfer of the results into practice. The two modelled OWP and the corresponding service ports match two OWP situated in the German North Sea. Furthermore, the central warehouse is situated at a feasible location between the two harbors. The OWT is composed of 17 different parts. The occurrence of a failure is modelled using a Poisson-distribution. If one of the parts fails, a failure notice is sent to the control centre, and the OWT is out of order until the required spare part is delivered. It is assumed that with the help of condition monitoring, the required spare part needed is always identified correctly and that only one spare part is needed per failure.

The model includes 17 different types of spare parts matching the components of the OWT. The spare parts are divided into three categories. Category A encompasses small and light spare parts which can be transported with the helicopter as well as the CTV. Category B includes all components that can be lifted with the board crane of the OWT; they are transported with the CTV. All the components which can only be transported with a crane vessel makeup category C. The different spare parts are implemented as variables which can be exchanged between the different agents and transported by them.

The material flow starts at the warehouse agent. Here all the spare parts are stored. The model allows for all the spare parts to be either stored in one central warehouse which is supplying both OWF or in two decentral warehouses situated directly at the service harbours. The warehouse operates using a reorder point (r, q)-policy.

The next agent in the model is the control centre. It is central for the information flow because all information comes together here. The control centre is receiving the failure notice from the OWT and then forwarding the order to the warehouse where the required spare part is stored. Additionally, it receives the weather forecast and determines which means of transport can leave the harbour to execute repairs on the OWT each day.

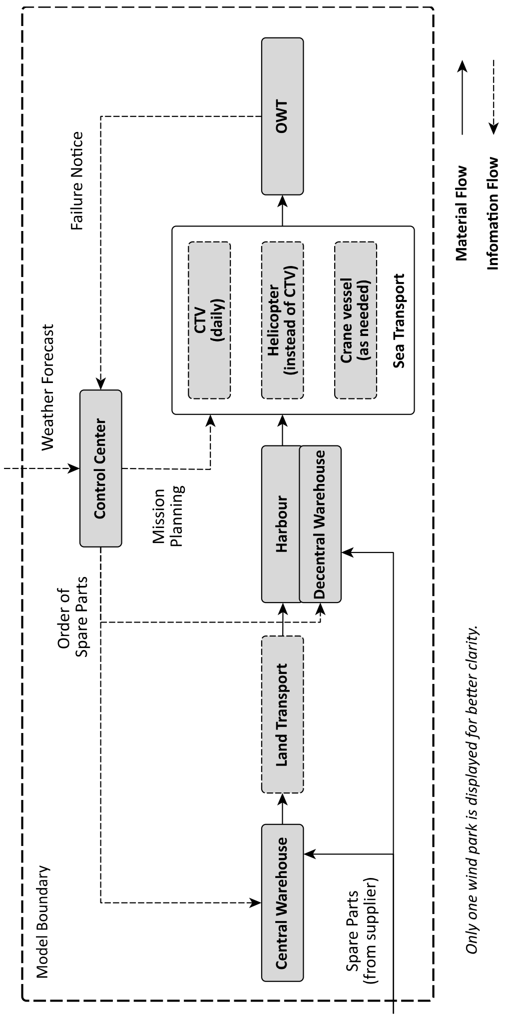

Figure 1: Overview of the Agent-Based Model including Material and Information Flow

For the transportation of the spare parts four different means of land and sea transport a modeled. At land daily pick-ups of spare parts from the central warehouse are assumed e.g. by logistic service providers and modeled by one agent. At sea the means of transport are based on those used by the offshore wind industry in practice for shore-based maintenance (e.g. GL Garrad Hassan, 2013; Münsterberg and Jahn, 2015). They are represented by three different agents (Endrerud, Liyanage and Keseric, 2014). The CTV is the standard mean of sea transportation, and it is assumed that it can carry enough spare parts and personnel to repair on average, three OWT per day. If the CTV cannot operate due to bad weather, but the weather is suited for the helicopter, it shuttles repair crews and spares to two OWT per day. It is assumed that both vehicles are available daily and operate if a window of operation larger than 6 hours is available. The crane vessel, however, has a waiting period of three months after the failure of the wind turbine and leaves the harbour if an operation window of 24h is available (Dalgic et al., 2015).

4.2 Data collection

In total, 16 parameters are needed for the model. Twelve of these are constants since they have no central influence on the land supply chain, which is the central focus of the analysis, and their values can be taken from the literature. Nine of these parameter are listed in Table 1, which define the operation of sea transport.

Table 1: A Key Figures Sea Transport (Münsterberg and Jahn, 2015)

Sea Transport	Weather Restriction	Value	Spare Parts
CTV	Significant wave height	1,5 m	A,B
Crane vessel	Significant wave height	2 m	C
Helicopter	Wind speed	17 m/s	A

The other three concern the different spare parts (see Table 2). The data for these are merged from different sources (Gayo, 2011; Dewan, 2014; Lindqvist and Lundin, 2010). The components with the highest failure rates are identified and chosen for the model. They are assigned a failure rate, which is calculated proportionately of the overall failure rate. The other parameters are the replenishment time and the price which are taken from Dewan (2014) as well as Lindqvist and Lundin (2010).

Table 2: Overview Spare Part Categories

Spare Part Category	Number of Parts	Share of Overall Failure Rate	Replenishment Time	Spare Part Price [€]
A	8	0.465	1 or 2 weeks	200 - 1,500
B	7	0.501	1 or 2 weeks	500 - 10,530
C	2	0.034	10 weeks	100,000 - 113,000

The remaining four input parameters are variables which are assigned different values using scenario analysis (see Figure 2). The storage level for the different spare part categories is alternated to enable a comparison of central and decentral storage. Scenarios with a helicopter and without helicopters are run because both supply chain setups are typical in practice. The other two variables: *overall failure rate and delivery time from the central warehouse are varied in the different scenarios to verify the assumptions made. The values for failure rates of OWT vary significantly between the different publications, and it depends on the average wind speed, drive train as well as the climatic conditions* (Faulstich, Hahn and Tavner, 2011; Carroll, McDonald and McMillan, 2016)*. So for the base scenario, overall failure rate per OWT per year is assumed to be 4, and delivery time from the central warehouse to the service harbour with 48h. To be able to determine the influence of this assumption on the results for both variables, high and low scenarios are run increasing or rather decreasing the values by 50 percent.*

A two-stage experiment (see Table 3) is designed, which includes all relevant scenarios but excludes irrelevant scenarios to reduce the number of overall simulation runs. In stage I, the optimal storage level for the heavy-duty (category C) components is determined and set to this value for all the simulation runs of stage II. This is possible since the supply chain of category C spare parts is independent of the supply chain of the other two spare part categories. In the following section, the results of these simulation runs will be discussed.

Table 3: Input Variables of Different Scenarios

Stage			**Storage Level**			
	Overall Failure Rate	Delivery Time	A	B	C	Helicopter
I	2, 4, 6 [/OWT/y]	48 [h]	Central/ Decentral	Central/ Decentral	Central/ Decentral	Yes
II	2, 4, 6 [/OWT/y]	24/48/72 [h]	Central/ Decentral	Central/ Decentral	Central	Yes /No

5 Results

In order to enable a comparison of central and decentral storage strategy for spare parts for offshore wind turbines, the profit margins for the two alternatives are first calculated and then compared in this section. Also, the Mean Time to Repair (MTTR) is calculated, which is an essential measure of the efficiency of the offshore wind supply chain and helps to explain the results.

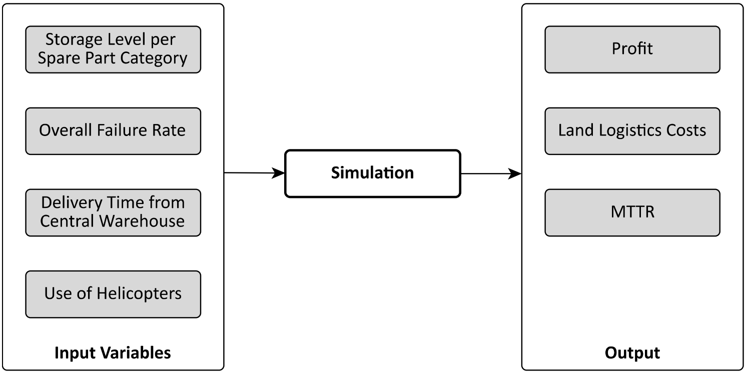

Figure 2: Input Variables and Output of the Simulation

Figure 3 shows the detailed calculation of the profit margin. It is calculated as the difference in revenues during the OWP lifetime minus the land logistics costs. The calculation only takes into account the land logistics costs, since only here are changes made to the supply chain setup. It is assumed that the water-side costs do not change, as the number of OWT failures and, accordingly, the number of repairs do not change. The revenues are calculated as the product of the total energy produced during the lifetime multiplied by the electricity price. The electricity price is set at 10.4 ct/kWh and assumed to be composed of a mixture of subsidized and non-subsidised purchase (Balks and Breloh, 2014). The power generated depends on the wind strength and the power curve of the Siemens SWT 3.6-120. The shortest term forecasts provided from the German Meteorological Service (DWD) for the locations of the two OWPs from 2013-2017 are used (four times during the 20 years of OWP lifetime) as the basis for determining the produced power. Thus, the number of functioning OWTs and the prevailing wind speed per OWP can be queried hourly in the simulation and the power generated can be determined.

The land logistics costs are calculated as the product of *storage costs* plus *transport costs* plus *order costs*. The *transport* and *order costs* are calculated using a fixed cost rate per order. The order cost rate is 400€ for both central and decentral storage. The transport cost rate varies for the different spare part categories: A: 23,11€, B: 42,09€, C: 811€ and is charged individually for every delivery of a spare part to the service harbor (Bundesverband Materialwirtschaft, Einkauf und Logistik, 2015). The storage costs are calculated as the product of the storage cost rate multiplied with the price of the spare part, the average stock level of the spare part and the duration of the simulation. In this case, the storage cost rate is assumed to be 28.7%, which is the usual rate for service providers (Bogaschewsky et al., 2012). All costs are individually determined per simulation run for each spare part category.

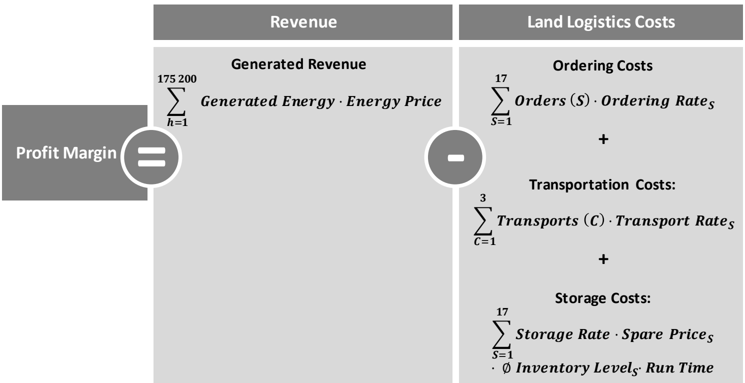

Figure 3: Calculation of Profit Margin

The MTTR is also determined for each spare parts category. It is calculated as the ratio of the sum of the downtime caused by a spare part category over the lifetime divided by the number of faults in this category during the lifetime:

$$MTTR_i = \frac{\Sigma\, downtime_i}{\Sigma\, failures_i} \quad (1)$$

In the following, the results from the two staged experiment are presented. In total, 24 simulation runs were executed during stage I using the input parameters shown in Table 3.

A comparison of the central and decentral storage strategy for the spare parts of category C shows that central storage yields a higher profit margin (see Figure 4). This can be attributed to two effects. First, the land logistics costs are about half as high in the case of central storage compared to decentral storage. A closer look at the costs reveals that this difference can be primarily ascribed to a reduction in inventory. In comparison, the transportation costs that accrue in case of central storage are rather small. The primary effect, however, which explains most of the increased profit margin is the increase in revenue, which is generated by the OWP in case the heavy duty spare parts are stored in a central warehouse. These higher revenues can be attributed to reduced MTTR and higher availability in case of central storage.

For stage II, the storage level for category C spare parts is now set as *central* for all simulation runs. The other input parameters: Overall failure rate, delivery time, stock levels A and B, as well as helicopter deployment, are varied in the different scenarios (Table 3). This means that a total of 72 further simulation runs are carried out.

The results of stage II show that a higher profit margin can be achieved with decentral storage of the small and medium spare parts (Category A&B). Again, the land logistics costs are higher for decentral storage due to increased total inventory levels (see Figure 5). For the spare parts of category A and B, however, the revenue is increased, and the MTTR decreases in case of decentral storage. This increase in revenues is significantly higher than the increase in logistics costs, and therefore, the profit margin increases in the case of decentral storage. A more detailed analysis of the results shows that the profit margin is higher for decentral storage irrespective of the scenario.

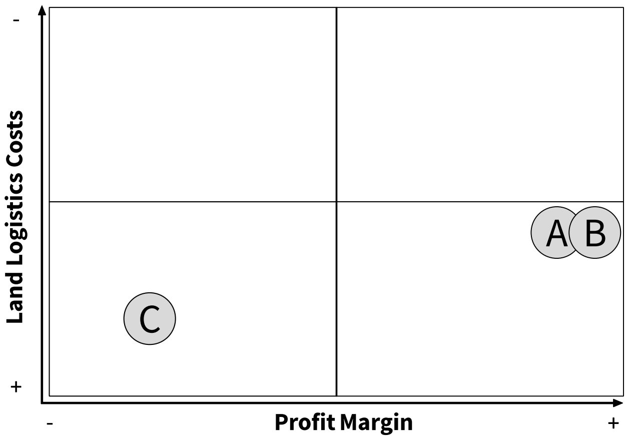

Figure 4: Comparison of Land Logistics Cost and Profit Margin of Decentral Storage compared to Central Storage

The MTTR has a significant impact on the availability of the OWT and therefore, on the profit margin during the O&M phase. Figure 5 shows how the profit margin decreases with increasing MTTR. The MTTR mainly depends on the waiting time for the spare part and the waiting time for a weather window for sea transport.

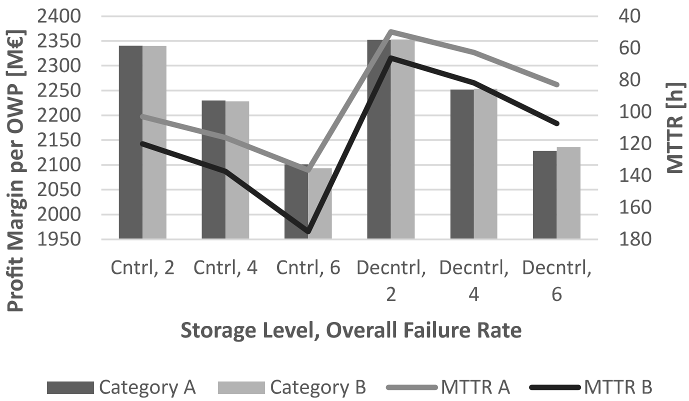

Figure 5: Profit Margin and MTTR for Spare Parts of Category A&B depending on Storage Level and Overall Failure Rate (averaged from 12 simulation runs)

In the model, the waiting time for sea transports does not change, but the waiting time for a spare part varies between the different scenarios. The analysis of the results shows that all the four input variables influence the MTTR. First, the MTTR increases if the spare parts are stored in a central warehouse as the spare parts have to be delivered to the service harbour. Second, the MTTR increases with the failure rate. This can be explained with longer waiting periods for sea transport as its capacity is limited. Additionally, the Figure shows that the MTTR of category A components is always shorter than that of category B, as these spare part can be transported by helicopter in addition to the CTV. Third, the deployment of the helicopter does influence the overall MTTR because it allows for additional repair missions in the OWP compared to only using a CTV. Fourth, increased delivery time from the central warehouse leads to an increased MTTR.

In order to verify the assumptions made about logistics and spare parts costs, a sensitivity analysis is carried out. This shows that the results are stable as even a doubling of costs does not influence them. The evaluation of the different scenarios also shows that an increase and decrease of the delivery time from the central warehouse and the overall failure rate by ± 50% does not influence the result.

6 Discussion of results

The results show that the MTTR is a moderator between the spare part strategy used and the revenue of the OWP. If the MTTR increases, the availability of the OWT decreases, and so does the revenue from the OWP. Other authors have also stressed the relevance of this parameter in the past, for example, in connection with the accessibility of the OWT (e.g. Dalgic et al., 2015). The results show that the causes of the MTTR changes vary depending on the characteristics of the spare parts.

For spare parts transported with the helicopter or CTV, the MTTR decreases in the case of decentral storage, since in this case the spare parts are directly available at the service port and the availability is not delayed by a delivery from a central warehouse. Spare parts transported with a crane vessel, on the other hand, are subject to an increase in MTTR due to increased stock shortages in decentral warehouse scenarios. Due to the higher storage costs and lower failure rates, inventories for of the heavy-duty components are only minimal, and the central storage allows for better absorption of peak demands while at the same time reducing storage costs. Since these components have a long replenishment time, shortages have a particularly drastic effect on MTTR. Also, the waiting time for a crane vessel is longer than the delivery time from the central warehouse, so the extension of the delivery time if stored at a central warehouse does not affect the MTTR.

For spare parts transported by CTV or helicopter, it can be seen that the increase in profits due to higher availability outweighs the higher logistics costs. This trend becomes particularly apparent with an increasing number of turbine failures, as the MTTR gains significance with a larger number of failures. In the future, this effect will gain even more relevance by increasing the power of the individual WTGs, since a more significant power potential remains unused in the event of a WTG failure. This shows that it is essential for the operators to ensure the high availability of spare parts because resulting in additional costs are outweighed by the increase in revenues.

The developed model assumes a local separation of service ports of the two OWPs. If, however, several OWPs are supplied from one service port, cost savings can be achieved by merging the warehouses without negative influences due to a longer delivery period.

The results are limited due to the characteristics of the model and the poor availability of data. The model includes only a reduced number of spare parts without reducing the number of defects per WTG. This means on the one hand that the failure rate per component is increased, on the other hand, that the number of spare parts in stock is reduced. The reduction in the number of components also means a reduction in the total stock. An increased number of components with the respective safety stock in the warehouse also means an increase of the total stock and thus of the storage costs. The average land logistics costs calculated are only about half as high as values from the literature. However, doubling these costs does not alter the results presented.

The reduction in the number of spare parts in the model also means that no components with a lower error rate than the C components and high storage costs are included in the model. After evaluation of the results, this type of spare parts appears to be suited for central storage.

Future research on spare part management for OWP could use other criteria for the division of the spare parts. The most fitting seems to be failure rate and storage cost of the spare parts. Nevertheless, the model showed that it was suitable to answer the research question.

7 Conclusions

In this paper, the influence of the spare parts strategy on the LCOE of Offshore Wind Parks is investigated. For this purpose, an agent-based model of a supply chain for spare parts for two offshore wind parks is developed including three spare part categories and the possibility of central and decentral storage. The results show that the correct spare parts strategy can help to reduce the LCOE of Offshore Wind. The main effect of the right spare part management, however, lies in the maximization of revenues through an increase of the Mean Time to Repair rather than in the reduction of costs. This increase in revenues leads to higher economic feasibility of offshore wind projects. The study highlights again how essential the O&M phase of the OWP is since it is the only phase during the lifetime of an OWP where revenues are generated.

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II.
Port Logistics

Simulation-based Optimization at Container Terminals: A Literature Review

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Purpose: While simulation-based optimization has been discussed in theory and practically employed at container terminals, the different publications in this field have not yet been presented and compared in a structured manner. This paper gathers the latest developments and examine the similarities and differences of the provided approaches. Furthermore, research gaps are identified.

Methodology: The recent literature of simulation-based optimization on container terminals is examined using a mapping review approach. Emphasis is laid on the covered problems, chosen meta-heuristics, and the shapes of the solution space.

Findings: In the applied literature of container terminals genetic algorithms prevail, both for scheduling problems and for the determination of discrete and/or continuous parameters. Because of the no-free-lunch-theorem for optimization, it is open whether the chosen optimization approach serves the purpose best.

Originality: To the best of our knowledge, the existing literature regarding simulation-based optimization at container terminals has never been addressed in a detailed overview. The elaborated comparison of the different publications leads to further research directions

Keywords: Simulation-based Optimization, Simulation-based Optimisation, Container Terminal, Maritime Logistics

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1 Introduction

In globe-spanning supply chains, maritime container terminals are of major importance. In terms of volume, over 80% of the world merchandise trade is handled by ports while in 2017 17.1% of global trade volumes were containerized (UNCTAD 2018). Container terminals need to run smoothly and cost-efficiently both for the economy depending on the transported goods and the terminal owners to stay in competition. Therefore, container terminal operations have been an active field of research for a long time (Steenken, Voß & Stahlbock 2004; Gharehgozli, Roy & DeKoster 2016). One major obstacle the authors present is that container terminals differ from each other in their terminal layout, the employed equipment, and the level of automation and digitalization, to name a few. This increases the difficulty to generalize insights of case studies and to transfer solutions and best practices between container terminals. On the other hand, container terminals will need to change and learn from the success stories of others in order to stay competitive. A continued market concentration in liner shipping allows shipping alliances to exert high pressure on container terminals (UNCTAD 2018).

The sheer complexity of a container terminal as well as the lack of generalizability for results obtained from a specific field study make it necessary to limit oneself on certain aspects. Some study fields have been of special interest, such as the Berth Allocation Problem (BAP), the Quay Crane Assignment Problem (QCAP), or the Quay Crane Scheduling Problem (QCSP) (Stahlbock & Voß 2007). Bierwirth & Meisel (2010) show that in literature there are use-case-specific assumptions, like spatial con-straints (discrete, continuous or hybrid berth layout), knowledge about arrival times in advance, whether ships have a strict time schedule etc. Furthermore, while some publications focus on a single problem (Dai et al. 2008), others perceive this as too narrow and formulate an integrated problem consisting of several parts (cf. Liang, Huang & Yang 2009). Many of these problems have been shown to be NP-hard, which is a major challenge (Steenken et al. 2004). While exhaustive search is theoretically possible, in many areas it has shown to be too time-consuming for practical appli-cation (Woeginger 2003). Hence, for real-world applications approximations need to suffice (Bierwirth & Meisel 2015).

Among others, sufficiently good input parameters can be estimated by using simulation-based optimization. For the same problem, different optimization algorithms can be used. This leads to the underlying question of this paper: Which algorithm(s) lead(s) to the best results under limited resources? In the following section, first more background on simulation-based optimization and related work is provided. In Section 3, the methodology is described. The results are presented and discussed in Section 4. Finally, in Section 5 conclusions are drawn.

2 Background and Related Work

The term "simulation-based optimization" is the key concept of this publication. Depending on the publication, different definitions or informal descriptions are used for the same term. In the following, first a definition for simulation-based optimization is provided. Afterwards, previous related publications are presented.

2.1 Simulation-based Optimization

Zhou et al. (2018) define simulation-based optimization as a method "to evaluate the performance of the system for a given configuration, while the optimization algorithm explores alternative configurations in the solution space and identifies the optimal setting". In this publication this definition is narrowed: Simulation-based optimization is a procedure to examine the most promising subset of all available solutions, i.e. parameter configurations. Therefore, multifidelity approaches such as presented by Li et al. (2017) are out of focus. To evaluate a specific parameter configuration, it is entered into a system which imitates (parts of) the container terminal. Such a system can be e.g. self-written code, or simulation software. For this publication it needs to meet the general definition of simulation as a "[r]epresentation of a system with its dynamic processes in an experimentable model to reach findings which are transferable to reality; in particular, the processes are developed over time." (Verein Deutscher Ingenieure 2014). Furthermore, simulation models can incorporate randomness to reflect the stochasticity of the real-world system. This surpasses simple deterministic evaluation schemes which can be evaluated within split-seconds.

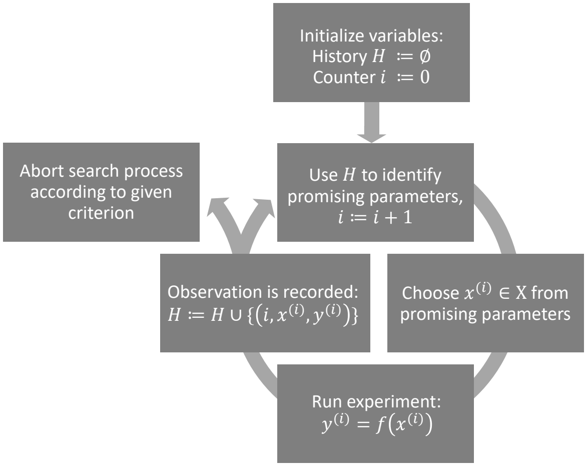

Figure 1: The cycle of simulation and optimization for simulation-based optimization

The concept of simulation-based optimization goes by different names, such as Simulation Evaluation (Figueira & Almada-Lobo 2014), Simulation Optimization (Amaran et al. 2016) or Optimization via Simulation (Xie, Frazier & Chick 2016). The integral assumption is that the system (here: container terminal) is too complex to directly apply mathematical programming methods. Stochasticity and interaction of the different subsystems hinder the observer to predict the impact of certain parameter configurations. The container terminal is assumed to be so complex that directly examining internal processes are fruitless.

Simulation-based optimization belongs to the larger family of black-box optimization procedures which are also referred to as meta-heuristics (Chopard & Tomassini 2018) or derivative-free optimization procedures

(Rios & Sahinidis 2013). Meta-heuristics are characterized by their universality. They can be used in many different disciplines for optimization, e.g. Simulated Annealing (SA) has been used for vehicle routing (Yu et al. 2017), job shop scheduling (van Laarhoven, Aarts & Lenstra 1992), or to define genetic structures of populations (Dupanloup, Schneider & Excoffier 2002).

A visualization of the concept simulation-based optimization can be seen in Figure . During the ongoing search process, in the history H the so far obtained observations are gathered. They guide the search by identifying promising parameters $\{x\}$, of which one, $x^{(i)}$, is chosen for a simulation experiment. The observed result $y^{(i)}$ is recorded and can be used to further guide the search. Usually meta-heuristics are formulated in a way that a stopping criterion needs to be explicitly defined. This can be defined e.g. by time, by number of cycles, the (lack of) obtained improvement within the last k evaluations.

The algorithmic steps to define a metaheuristic are by definition generic so that it can applied to new cases. Wolpert & Macready (1997) show that a metaheuristic which exploits the underlying structure of a certain optimization problem very well, leads to results worse than random results for another optimization problem. In other words, a meta-heuristic which picks the right next parameter configuration for every optimization problem can't exist. Still, empirical work can show that a certain meta-heuristic exploits the underlying structure of a specific problem better than another. This makes it inevitable to use large datasets, if available benchmarks, as well as reported results in comparable literature.

2.2 Related Work

A plethora of literature reviews deal with metaheuristics. Some, like Xu et al. (2015), used maritime logistics as a use case for showing the applicability of more general concepts. They present different optimization approaches, i.e. ranking and selection, black-box search methods that directly work with the simulation estimates of objective values, meta-model-based methods, gradient-based methods, sample path optimization, and stochastic constraint and multi-objective simulation optimization. For container terminals, recently only a subset of these options has been applied.

Zhou et al. (2018) reviewed different ways of how simulation and optimization had been jointly used in the field of maritime logistics. That included optimization tasks regarding the landside and waterside of the container terminal as well as the scheduling of vessels from the perspective of a ship owner. Based on the gathered literature, they differentiate between several modes, i.e. simulation-supported optimization, simulation optimization iteration, optimization-embedded simulation, and simulation-based optimization. The latter category is elaborated on in this publication.

Bierwirth & Meisel (2015) present the literature related to seaside operations planning. They focus on BAP, QCAP and QCSP and options of how to integrate them. A detailed problem classification for each of the problems provides an overview of past work in this field. Tactical planning is out of their scope and they do not examine the employed methodology, i.e. which algorithm has been used to search through which kind of solution space.

Several more general literature overviews about container terminals exist (Steenken et al. 2004; Stahlbock & Voß 2007; Carlo, Vis & Roodbergen 2014b, 2014a; Gharehgozli, Roy & DeKoster 2014, 2016; Dragović, Tzannatos & Park 2017).

Previous literature reviews follow two threads: Either the subject of simulation-based optimization is approached on a methodological level, then practical aspects of the container terminals often are less of concern. Or the subject is approached from a problem-based perspective and the employed methods are out of focus. This paper brings these threads together in order to create a new perspective.

3 Methodology

According to the literature review typology of Grant & Booth (2013), the following review is referred to as a mapping review. It targets at categorizing the existing literature about simulation-based optimization at container terminals. The focus of this study is to investigate which aspects of the container terminal have been optimized with simulation-based optimization, which search algorithms have been used, and how the shape of the solution space looks like. The latter can indicate which algorithms could serve as alternatives. Grant & Booth (2013) argue that mapping reviews are an appropriate tool for gaining an overview and identifying research gaps.

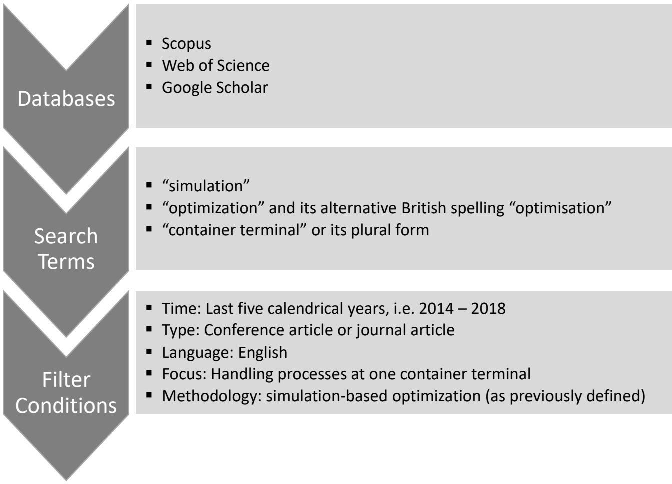

Figure 2: The process of searching the literature

The literature search process can be seen in Figure 2. Scopus, Web of Science, and Google Scholar are used to obtain the literature of interest. This review aims at covering a wide range of recent publications so that rare approaches are covered as well. The search terms to identify simulation-based optimization are "simulation", and "optimization" (alternatively in British English "optimisation"). This ensures that all the different terms for the same concept (as described in Section 2.1) are covered. Furthermore, the term "container terminal" (or "container terminals") needs to be mentioned in the publication. The search has been restricted to published conference articles and journal articles. The time range of interest is limited to the last five calendrical years, i.e. 2014 - 2018. Newer publications are ignored for the sake of repeatability. Each of the found articles needs to match the following criteria: (1) the publication is in English, (2) the scope of the examined system is restricted to one or several problems at one container terminal, (3) the examined problem solely examines the characteristics of the handling processes, and (4) the authors optimized one aspect of the container terminal, and (5) they used simulation-based optimization as previously defined for optimization.

The obtained literature is presented in a categorized manner in order to increase the comprehensibility. The distinction is based on the structure of the solution space and leads to two groups: (1) permutation space, or (2) an n-dimensional discrete or continuous space.

3.1 Permutation Space

For a set with k distinct items, k! permutations exist. The most common observed problem is to decide about in which order a set of tasks will be executed. In most cases, the permutation space can be restricted as constraints exist, such as dependencies between tasks. Still, with a growing size of the set, the solution space quickly turns intractable. At container terminals, plenty of well-examined scheduling problems exist (Steenken et al. 2004; Stahlbock & Voß 2007; Bierwirth & Meisel 2010, 2015; Gharehgozli et al. 2016). A set of resources of the same type, such as Quay Cranes (QC), Yard Trucks (YT), or Yard Cranes (YC), needs to be assigned to transport containers from a source to a destination. The major difficulty lies in determining which machine is paired with which task. These scheduling problems suffer from exactly that explosion of the solution space which is one of the reasons for a mostly sub-optimal employment of equipment at container terminals.

On a methodological level, the scheduling problems for the different types of equipment (i.e. QCSP, YCSP, and Vehicle Dispatching Problem (VDP)) share many characteristics. Hartmann (2004) defines a general scheduling model to "consist of the assignment of jobs to resources and the temporal arrangement of the jobs subject to precedence constraints and sequence-dependent setup times". The model is later applied to assign straddle carriers, automated guided vehicles, and stacking cranes to transportation tasks, as well as workers to jobs related to the maintenance of reefer containers. This encourages the perspective that the different scheduling problems can be compared on a methodological level, and approaches which have been applied for one scheduling problem might also be used for another.

3.2 n-dimensional Discrete and/or Continuous Space

When a researcher or practitioner is asked to optimize a container terminal without further constraints, plenty of alternatives exist. With each questioned design decision, the solution space grows exponentially. For the simple case of choosing between two levels for each considered factor (e.g. different strategies for each equipment type), for n different factors 2^n possible solutions exist. With an increasing amount of levels, this amount further increases. This makes the execution of a grid search quickly intractable. The choice of the most promising subset of the solution space is difficult because of the complex interactions of the different subsystems at a container terminal.
When planning the extension or modification of a terminal, different facets of a terminal are of interest. Often the effect of changes in the berth layout, yard layout, and gate and rail area layout on the behavior of the container terminal is of interest (Leriche et al. 2016; Kotachi et al. 2018). As a change

in one of them influences the performance of the others, the subset to evaluate must be chosen with care. Furthermore, the amount of equipment to purchase increases the levels to investigate and hence the size of the solution space tremendously. The solution space can be limited by examining only a coarse grid which seems relevant and promising to experts (Kotachi, Rabadi & Obeid 2013).

4 Results and Discussion

The literature search described in Section 3 discovers recent publications which have used simulation-based optimization at container terminals, covering lots of different problems, ranging from optimization tasks in everyday work life to supporting major investment decisions. Especially the short-term optimization tasks are described as some kind of scheduling problems, i.e. the solution is an efficient sequence of jobs. The long-term decision problems, such as layout determination and equipment purchases, are reflected by discrete or continuous values.

4.1 Permutation Space

In Table 1 the compilation of different simulation-based optimization approaches which deal with permutations is presented. In addition to the already mentioned scheduling problems, the Tug Pilot Assignment Problem (TAP), the Quay Crane Dual-Cycling Scheduling Problem (QCDS), the Storage Space Allocation Problem (SSAP), the Vehicle Dispatching Problem (VDP), and the Sequencing of Optimization Problem (SOP) are covered. The ampersand (&) indicates the integration of several problems. Mostly Genetic Algorithms (GA) are used, and second most Particle Swam Optimization (PSO). Here the ampersand indicates that two algorithms were intertwined. The algorithm on the left side is on the upper level, while the algorithm on the right side of the ampersand is on the lower level. Simulated Annealing (SA), Taboo Search (TS) and Beam Search (BS) are used less frequently. Evolutionary Algorithms (EA) are a superclass of GAs and share many commonalities. The solution space matrix is derived from the graphical or textual description of the solution representation. This was not necessarily the internal representation during the search process, e.g. the implementation following the BS methodology constructs the solution based on several sets. Furthermore, neighborhood definitions often needed for SA are not accounted for. Yet, the shape of the solution space determines which algorithms can be used. The number sign (#) followed by an equipment type represents the number of distinct machines - similarly for tasks, containers or facilities on the container terminal. Here, one- or two-dimensional matrices have been used. One-dimensional matrices decode the sequence of tasks and use specific schemes for the assignment to different machines. The second dimension is mostly used for distinguishing between different types of equipment or the different instances.

The literature deals with many different equipment scheduling problems (QCAP, QCSP, QDCS, YCSP, VDP, TAP), problems related to area usage (BAP, SSAP), and the determination of a sequence of how to optimize different problems at a container terminal (SOP). It can be seen that even when two publications cover the same problem, the way the results are obtained always differ. Not two publications work on the same problem with the same algorithm, and a solution space of the same shape. This makes it difficult to draw conclusions directly.

Table 1: Simulation-based Optimization in the Permutation Space

Reference	**Problem**	**Algorithm**	**Solution Space Matrix Dimensions**
Al-Dhaheri, Jebali & Diabat 2016	QCSP	GA	$\#QCs \times \#bays$
Arango et al. 2013	BAP	GA	$\#vessels\ x\ 60$
Cordeau et al. 2015	SSAP	SA, TS	$\#housekeeping\ tasks$
Gudelj, Krčum & Čorić 2017	VDP	GA	$\#tasks + 2 \cdot \#projects + \#equipment$
Haoyuan & Qi 2017	QCSP	GA, PSO, SA	$\#ship\ areas\ with\ tasks$
He, Huang & Yan 2015	YCSP	GA & PSO	$\#tasks \times 2$
He et al. 2015	VDP & YCSP & QCSP	GA & PSO	$\#tasks \times 3$
Olteanu et al. 2018	QCAP & QCSP	GA	$\#Q \times \#assigned\ cont's$
Said & El-Horbaty 2015	SSAP	GA	$\#storage\ blocks$
Supeno, Rusmin & Hindersah 2015	VDP	GA	$\#transp.tasks + \#YTs$
Zeng, Diabat & Zhang 2015	QDCS	GA & GA	$2 \cdot \#rows + 1,$ $\#cont's\ to\ load$
Zhao et al. 2015	SSAP	GA, PSO	$\#stacking\ instructions$

A yet untouched topic is the interpretation of the solution space. When decoding a single sequence into a schedule covering several machines, in literature many approaches exist. It remains an open question whether some encoding schemes have superior properties for the solution space exploration and exploitation. All solutions are represented by a one- or two-dimensional matrix. Often some of the complexity is delegated to problem-specific algorithms for fixing infeasible solutions as well as the encoding and decoding of the problem into actions in the simulation model. For PSO, one viable way is to translate the discrete space into a continuous space for the search phase and translate it back into the discrete space before translating the sequence into measurable actions inside the simulation model (He, Huang & Yan 2015a).

4.2 n-dimensional Discrete and/or Continuous Space

In Table 2, a summary of the reviewed studies is presented. The variable K_i simply represents a decision variable which is of continuous nature. The type of two decision variables could only not be verified for the publication of Leriche et al. (2016) because of a lack of provided details. This is indicated by an apostrophe. In the Table, different problems are in focus: Four of the publications deal with the terminal layout and equipment. In addition, parameters for a rail system or an empty container policy are tuned. Like in permutation space, GAs prevail. Other employed meta-heuristics are EAs, Scatter Search (SS), and Glow-worm Swarm Optimization (GSO).

Among the publications in Table 2, Kotachi et al. (2018) tunes the largest number of distinct facilities simultaneously, covering the berth layout (length of berth), yard layout (number of import and export rows, number of YCs per row) and the gate (number of lanes). Due to this complexity, first the sequence of the optimization tasks was solved in the permutation space (see the previous section). Four of the seven publications deal with block planning, general layout planning and equipment purchases. The decisions are of high impact and due to the differences between container terminals the answers of the studies can hardly be generalized. Yet a conceptual framework is of interest in the industry (Lin, Gao & Zhang 2014; Kotachi et al. 2018). For policy parameter tuning, the previously listed BAP is addressed again. Here, parameters of a decision support module are tuned (Ursavas 2015).

Table 2: Simulation-based Optimization in the n-dimensional Discrete and/or Continuous Space

Reference	**Problem**	**Algorithm**	**Solution Space**
Haoyuan and Dongshi 2016	Block Planning	GA	$\{0, 1\}^{36}$
Kotachi et al. 2018	Layout & Equipment	EA	$K_1 \times K_2 \times K_3 \times K_4 \times K_5 \times K_6 \times K_7$
Leriche et al. 2016	Rail system parameters	SS	$K_1 \times K_2' \times K_3'$
Sáinz Bernat et al. 2016	Empty container policy parameters	GA	$\mathbb{N}^2$
Shahpanah et al. 2014	Layout & Equipment	GA	$\mathbb{N}^4$
Ursavas 2015	BAP Priority Control Policy Parameters	SS	$\mathbb{R}^{\#vessel\ classes}$, $\mathbb{N}^{\#berths \times \#vessel\ classes}$
Zukhruf et al. 2017	Equipment	GSO	$\mathbb{N}^2$

Similarly, Sáinz Bernat et al. (2016) tune parameters which are used for an empty container policy. At this point, optimization works on a meta-level and does not optimize the actual problem anymore.
In total, in three out of seven cases GAs are used, and all search algorithms (i.e. GA, EA, SS, and GSO) are population-based meta-heuristics. Interestingly, at no point Random Search (RS) has been used as a baseline. RS has shown better search results than human-guided search processes in other domains (Bergstra & Bengio 2012). Any meta-heuristic needs to be better than random to contribute to the optimization process.

5 Conclusions and Future Research Directions

Several publications hardly vary the parameters which control the behavior of a meta-heuristic. In addition, little justification is given for the reason why a meta-heuristic has been chosen. This might be a very challenging task. If one knew the exact behavior of the complex system, one would not need simulation. If one knew sufficiently good rules of thumb for the decision problems at hand, one would not need optimization. Therefore, arguing for a specific meta-heuristic with specific parameter values is difficult. Sörensen (2015) argues that by deconstruction one can gain deep insight into how each of the components of a meta-heuristic work. Watson, Howe & Darrell Whitley (2006) showed how a tabu search algorithm can be examined by running different experiments. Such steps help to understand why certain performance measures are obtained - something that might be more helpful than just obtaining and reporting better scores. To give one example, He et al. (2015a) and He et al. (2015b) use GA & PSO while He

(2016) use GA & SA for different types of scheduling problems. The theoretical reasoning or initial empirical evidence for why in the third scientific contribution GA & PSO is not applied could be of further interest. In this regard, the research about meta-heuristics for maritime research problems is in its infancy.

5.1 Limitations of This Literature Review

The search was restricted to a short time range of five years, thus it could not detect developments over a longer time period. The search terms were chosen with care but the fusion of optimization and simulation goes by different names, so some publications could have stayed undetected. The large scope of covering all kinds of simulation in the scope of a single container terminal resulted in some typically reported optimization problems (see e.g. Gharehgozli et al. 2016) and some rather specialized issues, especially in the n-dimensional discrete and/or continuous search space. This wide range limits how the optimization approaches can be reasonably compared. For this reason, the contentual perspective is lacking, such as the practical and theoretical assumptions made, or how a found solution representation is exactly interpreted in the simulation model. In some publications, several intermediate solution representations were presented. This could not be sufficiently covered in the overview. Furthermore, similar optimization problems exist outside container terminals (Xu et al. 2015). The focus on one container terminal limits the covered literature and neglects problems which are similar in theory.

5.2 Future Research Directions

The aforementioned limitations create great opportunities for future explorations: When focusing on one problem (or a group of similar problems), by far more criteria can be examined and compared meaningfully. On the one hand, the contentual perspective needs to be elaborated. A fair comparison of different optimization strategies needs to take into account which conceptual model and simulation model have been developed and which assumptions have been made. On the other hand, the algorithms can be examined in more detail, including the algorithm selection and parameter tuning process.

In general, the search process of meta-heuristics needs to be further investigated. Sörensen (2015) advocates to intensify the research less on the pure performance of a meta-heuristic but more on the how and why. In this literature review, GAs have been used in 16 out of 25 publications. What is the reason behind that? How promising are other meta-heuristics? An in-depth analysis of the search behavior can possibly provide the reasoning for the selection of the most appropriate algorithm in future.

Only a few instances of meta-heuristics operating in the n-dimensional discrete and/or continuous space have been presented. As Kotachi et al. (2018) argue, this is one essential approach in the field of terminal planning. The same type of solution space has been of great interest in the automated machine learning community as well (Bergstra et al. 2011; Hutter, Hoos & Leyton-Brown 2011). It remains an open research question how well the meta-heuristics can be applied to simulation models. Different meta-heuristics alongside with different meta-heuristic parameters need to be empirically compared to gain more insights.

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Potential of Non-port Slot Booking Systems for TAS

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Purpose: Truck appointment systems (TAS) are a reliable method for seaport container terminals to reduce peaks in truck arrivals. Thereby, the operation costs for terminals and the waiting times for trucking companies are reduced. The focus of this study is to optimize TAS by analyzing and transferring the components of non-port time slot booking systems.

Methodology: A comprehensive systematic literature analysis is applied to identify the potential of non-port time slot booking systems. Three industries are identified whose time slot booking systems are well transferable to TAS. The most promising industry, the health care sector, and specific approaches are selected for a benchmark.

Findings: The results show that in particular the time window booking systems from the health care sector have a good transferability to TAS in ports. Of the approaches examined, the overbooking of appointments in fixed time windows was rated most positively in the benefit analysis.

Originality: Past studies usually treat TAS in ports as a completely new subject area. Findings from other industries are rarely taken into account. A systemic study on the transferability of selected approaches from other sectors has not yet been carried out for TAS.

Keywords: Truck Appointment System, Container Terminal, Benchmark Analysis, Health Care

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1 Introduction

Seaports have always played a special historical role in trade. Container terminals in particular have developed into the backbone of the national and regional economy. The introduction of Ultra Large Container Vessels in recent years resulted in a strong increase in the demands placed on container handling. Terminals are faced with the challenge of loading and unloading more containers in less time. One way to meet this challenge is to introduce management strategies aimed at avoiding bottlenecks (Ambrosino and Peirano, 2016). Furthermore, considerable traffic loads with increasing truck waiting and handling times and therefore reduced productivity of container terminals can be observed. Bottlenecks, producing truck congestion inside and outside the terminal, can lead to serious local environmental problems such as noise and harmful emissions, but also to major inefficiencies in various operations. The main cause of truck congestion is the fluctuating arrival pattern of trucks. This results in a situation where demand significantly exceeds supply or vice versa (Huynh and Walton, 2011). A well-established solution to mitigate the problems described is to implement a truck appointment system (TAS). With this, it is possible to increase the gate capacity without expanding the area. The terminal operator determines time windows when containers may be delivered and collected. The truck operators can then choose between the time windows. This enables optimum use of the terminal's capacities and prompt operation of the trucks (Li, et al., 2016). Various approaches can be observed as to how TAS can be designed to counteract truck congestion and the associated stresses. Nevertheless, so far no structured analysis on the different parameters of TAS and their effect on the efficiency exists. Furthermore, many

studies focus on TAS in ports as an isolated problem and do not use all the potential knowledge about time slot booking systems generated in years of research in other industries. This aspect has so far only been illuminated to a limited extent in literature on TAS.
The explicit aim of the present work is to answer the two following research questions:

1. Which systemic properties of non-port time slot booking systems in other industries are relevant for TAS in ports?
2. To what extent can the highlighted properties be transferred to TAS?

In order to answer the first research question, a systematic literature search is carried out to identify the potential of non-port time slot booking systems. The second research question implies the examination of the highlighted components for their transferability in the TAS under consideration. First, in Section 2 the background is illuminated to introduce the topic of container terminals in general and TAS especially. The current state of research is presented as well. Section 3 shows the results of a systematic literature review and shows possible approaches to optimize TAS from other industries. Section 4 presents a benchmark analysis for one chosen industry and evaluates the utility for the presented solutions for implementation in TAS. Subsequently, in Section 5 a conclusion and an outlook are given.

2 Truck Appointment Systems at Container Terminals

In the following section, the overall structure and current developments of container terminals are presented. Afterwards, the functionalities of TAS and their interference influences are shown. Lastly, the state of research for TAS' characteristics is determined as a basis for this study.

2.1 Container Terminals: Recent Developments

International trade increases steadily since 2010, with maritime transport representing around 90 % of the global trade volume. Seaports support globalized production processes and their integration into the world economy. In line with this development, the container handling volume increased from 560 million Twenty Foot Equivalent Units (TEU) in 2010 to 752 million TEU in 2017 (UNITED NATIONS CONFERENCE ON TRADE AND DEVELOPMENT, 2019).

Economies of scale in transport are increasingly used to cope with rising competition and transport volumes. Today's container vessels have a capacity of over 21,000 Twenty-foot equivalent unit (TEU). Since the introduction of Post-Panamax container vessels in 1992, ship sizes quadrupled, whereas construction costs do not differ significantly from those of a Panamax class ship from the 1990s (Haralambides, 2017). As a consequence, the number of containers to be unloaded per port is increasing, thus increasing load peaks for container terminals and their hinterland.

The core task of a terminal is to handle containers between different means of transport. It can be stated for all terminals that they consist of at least three elementary subsystems (Kim and Günther, 2007):

1. sea-side (handling area between terminal and ship and vice versa)
2. container yard (container stacking area)
3. land-side (handling area between terminal and means of land transport).

The sea-side functional area is usually equipped with ship to shore cranes to load or unload the sea container vessels, feeder ships or inland waterway vessels. The container yard offers storage capacities for import, export and transshipment containers. The landside superstructure consists of truck and train handling areas in conjunction with the physical entrances, the gates. The hinterland handling operations are designed to efficiently control access to and from the terminal (Steenken, Voß and Stahlbock, 2004).
The gate represents a bottleneck whose efficient operation is important to the terminal operator. Due to the close connection of all three functional areas, the gate processes also have an effect on the other functional areas (Dekker, et al., 2013). According to Abe and Wilson (2009), if traffic congestion in ports increases by 10 %, maritime transport costs will rise by 0.7 %. Furthermore, during the waiting times in queues in front of the gate, the truck aggregates are idling and continuously emit exhaust gases that are harmful to health and the environment.
Possible measures to reduce the congestion in front of the gate are:

- Enhance the physical capacity of the existing gate complex by increasing the number of gates and truck access lanes.
- Increase gate capacity by accelerating gate service time by using management solutions and information technologies, e. g. automated truck registration and container identification systems and

cameras to check the physical condition of the container (Bentolila, et al., 2016).

- Extend gate opening combined with a differentiated pricing system to reduce peak times at the gate and shift to less busy times of the day (Bentolila, et al., 2016).
- Construct a pre-storage area or marshalling yard (Gracia, González-Ramírez and Mar-Ortiz, 2016).
- Diversify truck arrivals by introducing a TAS to regulate the number of trucks that can enter the terminal (Bentolila, et al., 2016).

However, extending gate opening hours is not always possible and purposeful, since driving bans exist for trucking companies. Infrastructural measures represent long-term solutions that can have a strongly limiting effect due to the sometimes tense space situation in the port area and the associated high infrastructure and maintenance costs.

In contrast, TAS are implemented more easily. The aim is to achieve a more even distribution of arrivals over the available time by better planning and scheduling of the arrival patterns of the trucks in order to reduce peak loads. The concrete implementation strategy of a TAS varies from case to case. The design and implementation of these technical instruments must always be adapted to the individual circumstances of each terminal in order to play to its full potential (Ambrosino and Peirano, 2016).

2.2 Functionalities of Truck Appointment Systems

In literature, there are various terms used to describe the optimal flow control of trucks at terminals. Examples are the terms "terminal appointment system" (Morais and Lord (2006)), "gate appointment system" (Giuliano and O'Brien (2007)), "vehicle booking system" (Davies (2009)), and "truck

appointment system" (Huynh, Smith and Harder (2016)). Since the terms are largely used with the same meaning, the term truck appointment system is chosen, which is most frequently used in literature and practice. Gracia, González-Ramírez and Mar-Ortiz (2016, p. 405) define TAS as follows:
" […] technological platforms designed to coordinate and balance truck flows at ports, supporting planning and scheduling truck arrivals, such that truck arrival patterns may be more evenly distributed by reducing peak hour arrival patterns. The general idea is that port terminals may receive advanced information for better planning of the operations at the yard and this may reduce truck turnaround times as well as waiting times of trucks at the gate.“
Despite deviations due to specific local conditions, the following functionalities of TAS can be recorded according to Chen, Govindan and Yang (2013):

1. determining the quota
2. booking a time window
3. registering containers and trucks
4. checking the specific data at the gate
5. administration

By determining the quota, the respective TAS can limit the number of container inputs and outputs to be booked during the operating time of the gate. Depending on the requirements of the terminal, the operating time of the gate can be divided into hourly or daily shift segments or days (Huynh and Walton, 2008). Based on the defined quota, the trucks book a time window (Geweke and Busse, 2011). Registration and verification are usually

carried out in the gate area of the terminal. The registration of the delivering truck serves to compare internal system data for security purposes and prevents trucks from gaining access to the terminal without prior notification. The administration includes the functions of security and controlling. The identity of container owner, trucking company and truck driver must be determined and recorded to avoid legal problems.
Furthermore, various interference influences on TAS need to be considered (Figure 1)

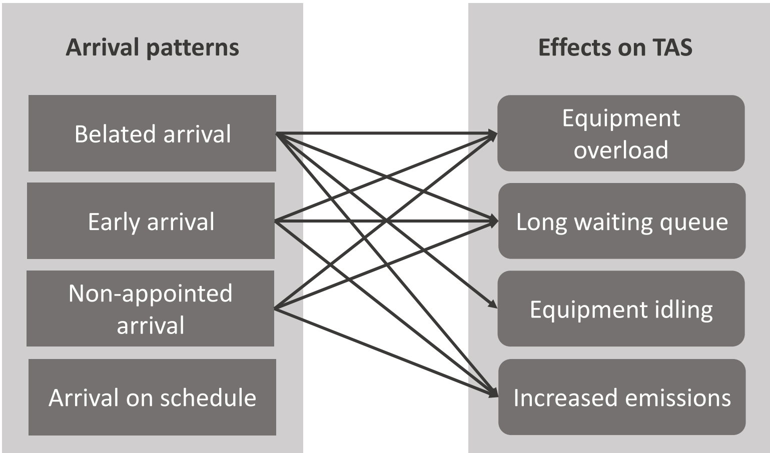

Figure 1: Interference influences on TAS (based on Li, et al. (2016))

If the trucks reach the terminal late or prematurely, the terminal equipments' capacity might either be not sufficient or too high. This leads to long queues in front of the gate or hinder planned maintenance or restacking operations. This disruption can become even more serious if additional arrivals are not agreed. If these types of arrivals accumulate, the terminal will be confronted with additional burdens in the handling of trucks, which can have serious consequences for the punctual handling of other trucks and lead to problems in terminal operations (Li, et al., 2016).

2.3 State of Research

TAS at container terminals have been increasingly investigated since 2004. The focus is mostly on the benefits generated for container terminals. Furthermore, it is noticeable that mostly only individual terminals were considered and different characteristics were examined there. A systematic investigation of various TAS parameters across terminals has not yet taken place (Lange, Schwientek and Jahn, 2017). A good overview of existing TAS worldwide can be found in Huynh, Smith and Harder (2016). Huiyun, et al. (2018) show examples of important focal points in TAS research. Innovative approaches that consider other actors, such as trucking companies, in addition to container terminals can be found in Caballini, Sacone and Saeednia (2016); Namboothiri and Erera (2008) or Rajamanickam and Ramadurai (2015). Here, too, the focus is on individual ports or individual parameters, which are examined in more detail.
Furthermore, TAS are mostly treated as completely new innovations or at most compared with other, already existing solutions in other ports (Lange, Schwientek and Jahn, 2017). The insights gained in other industries for comparable applications are very rarely taken into account. The only study known to the authors in this respect is by Huynh and Walton (2011), in which the similarities and differences between time window booking systems in the health system and in ports are compared briefly. This area has been chosen because it has the greatest similarities to TAS in ports. These similarities include the randomly fluctuating demand figures, changing

processing times, a high no-show quota and a high importance of punctuality.

It can be stated that TAS differ greatly and that there is no reproducible template for a successful TAS. Furthermore, little experience from other industries has so far been transferred to TAS in ports. It can be assumed that valuable insights are possible by this broader approach.

3 Systematic Literature Analysis

In order to investigate the potentials of non-port time slot booking systems for TAS in ports, a systematic literature analysis is carried out. The literature databases Scopus and Web of Science are used, which contain the research output from the fields of natural sciences, technology, medicine, social sciences and the humanities. In order to obtain as broad a spectrum of results and topics as possible, synonyms and extensions of the term 'Appointment System' are used. The search query in the two databases Scopus and Web of Science therefore looks as follows: ((„Appointment“ AND „System“) OR („Time Slot“) AND („Management“ OR „Booking“ OR „Scheduling“)).

3.1 General Results

Due to the high hit rate of 9,566 publications, the search result must be further restricted to enable evaluation (Figure 2).

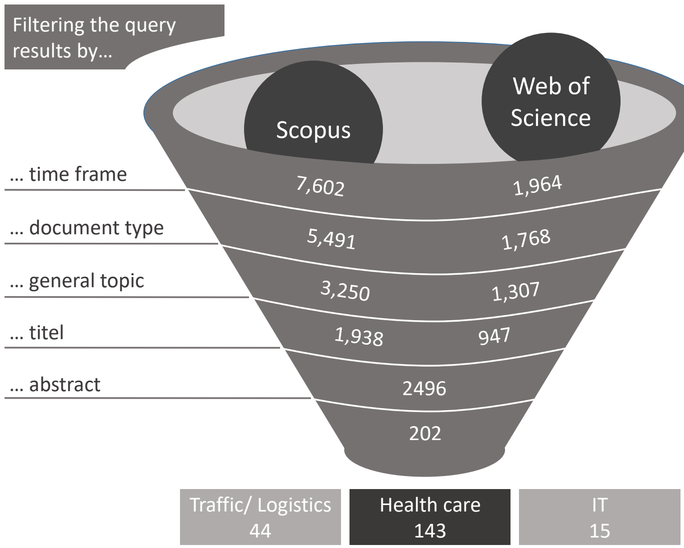

Figure 2: Number of publications in different filtering stages

The time frame of the search query is set to the period 2005 - 2018. Subsequently, the available literature is restricted exclusively to journal articles. Furthermore, all publications are excluded from the search results which focus differ greatly from time window booking systems that are used, discussed, or evaluated in relevant subject areas. Finally, the remaining publications can be categorized to the main subject areas. Articles that cannot be assigned to any of these main areas will not be considered any further. The subject areas can therefore be divided as follows:

- Healthcare: 143 publications
- Computer Science: 15 Publications

- Transport/Logistics: 44 Publications

As a result of the systematic literature analysis, the following aspects can be summarized: In science, time window booking systems are considered for numerous areas. However, these were quantitatively most frequently examined in health care. The number of scientific publications in this area is significantly higher than in the other two areas examined. The complex of topics of the health care system can be further subdivided into strategic, tactical and operative levels, which is borrowed from the entrepreneurial planning horizon. From the literature analysis carried out, a continued discussion of other benchmarking potentials with the topics of information technology and logistics/transport is not considered to be effective. The reasons are the low or even non-existent systemic similarities, such as the demand volatility of system-specific capacities, service times of different durations and the sudden loss of demand due to non-appearance. Furthermore, against this background, a continuous focus on the operative health care system is not appropriate either. The short time horizon of the operative planning horizon, by definition, cannot be taken into account for benchmarking because it is characterized by a fast and flexible handling of different patient classes on the demand side.

3.2 Health Care Sector

In this subsection the most promising three approaches to optimize time windows in the health care sector are presented. All of this approaches have a tactical/ strategic planning horizon.

Open Access

It is customary for patients to arrange appointments several weeks or even months in advance.

The so-called Open Access approach represents a compromise between a physician's break time and the patient waiting time by arranging appointments for patients with urgent needs, which are not urgent enough for the emergency department (same-day patients). The number of routine patients can be determined in advance, but the number of same-day patients varies. The appointment planner will assign appointments to patients. The treatment time cannot be specified in advance. In addition, it is not certain that same-day patients will actually appear at their appointment. However, Chen and Robinson (2014) and Robinson and Chen (2010) demonstrate that the Open Access approach qualitatively exceeds traditional scheduling in the vast majority of cases. Their articles focus on the optimal combination of routine and same-day patients. They also show how these two groups can be planned throughout the day and how the same-day patients' treatment outlook affects the appointment times of routine patients (Robinson and Chen, 2010; Chen and Robinson, 2014).

Defragmentation

The standard procedure for scheduling appointments is to divide the opening hours of a clinic into a finite number of non-overlapping time windows. Each time window is defined by a fixed duration. After an appointment request, the appointment planner first estimates the number of required standardized consecutive time windows. In the subsequent step, the system searches within the schedule for possibilities to book these time windows. If appointments are available, an offer of different appointments is made to the patient. According to Lian, et al. (2010), the conventional procedure for creating appointment plans systematically leads to inefficiencies. Their research therefore focuses on controlling the scheduling process through schedule defragmentation. Consequently, a procedure is recommended that displays all available appointment proposals when a patient requests an appointment. The proposed appointments are listed with regard to their defragmentation effect on the overall system. It turns out that the fragmentation of the time schedule can be effectively reduced by the increased cooperation of the patients with the doctor's practices or clinics. As a result, the capacity utilization of the practices or clinics will be higher (Lian, et al., 2010).

Overbooking

No-shows usually result in performance losses in capacity utilization and productivity for health service providers. To reduce no-show effects, appointments are often overbooked. However, this strategy inevitably leads to overcrowding, more overtime and longer waiting times. A variation of the time window length allows greater flexibility in when treatments can be started. The flexible handling of the start of treatment is particularly suitable in an environment where patients can be informed of exact appointment times via mobile phone applications. Chen, et al. (2018) study the impact of three types of time window structures on the efficiency of healthcare systems: Time windows with fixed length, with dome patterns and with flexible appointment start times. The aim is to determine the optimal overbooking allocation and slot interval structure in response to the uncertainties that may arise from the different treatment times of patients and their possible no-show behaviour (Chen, et al., 2018).

4 Benchmarking Analysis

In this section, a systematic benchmark process is presented using selected TAS processes. Industry-external benchmarking is used to answer the research questions. Compared to industry- and competition-related benchmarking, industry-independent benchmarking offers new perspectives and more innovation potential. Non-monetary parameters are used for the evaluation, for which a utility value analysis is subsequently carried out. This ultimately results in a weighted number of measures that can be used as recommendations for further improvement of TAS.

4.1 Selection of the Processes to be Examined

Several processes offer potential for optimization when implementing a TAS. In the further course of the work, two of these processes will be taken into focus, namely 'booking a time window' and 'setting the quota'.

The process 'booking a time window' is selected because the handling of no-shows can be improved. Influencing factors such as traffic congestion, full closures of motorways, construction sites or accidents can lead to short-term failure of booked time windows. Moreover, authors such as Huynh and Walton (2008) take walk-ins into account in their approaches. In the context of TAS, these are trucks that gain access to the terminal without an appointment. The productivity of the terminal can only be maintained at a high level if the failures are countered accordingly. To achieve this, TAS often use the 'Open Access' concept (Ambrosino and Peirano, 2016). However, little is known about the practical design of the approach from literature. In addition, the time frame in which the trucks are to be dispatched on

the terminal premises in front of the container storage facilities must be examined more closely in this context. The time frame can range from half an hour to 24 hours (Huynh, Smith and Harder, 2016).
Furthermore, another focus is on the process of 'determining the quota'. In this process it is possible to use the given terminal capacities more efficiently in order to further increase productivity and thus the quota. The time window lengths and the handling of individual time windows are dealt with. The present benchmark process focuses on the approach of Huynh and Walton (2008), how time windows for the arrival of trucks are divided. This approach divides the operating time of the terminal into evenly distributed time windows. The time window size is then used as the basic unit.

4.2 Determination of Optimization Potential

This subsection deals with the analysis of the two critical processes of time window booking and quota setting. The performance gaps of the selected processes are determined in comparison to the health care system and examined with regard to their causes.
The practices of short-term removal of booked appointment windows or exchange of agreed appointment windows create gaps in the terminal's schedule. In particular, by taking into account the needs of the haulage companies, a minimum degree of flexibility can be guaranteed. This flexibility, however, entails the risk of productivity losses due to the fact that time windows can no longer be filled.
The time frame within which the container is to be collected or brought can vary from half an hour to 24 hours with a certain tolerance (e. g. half an hour). However, when setting up large time frames, the procedure leads to exactly the type of behavior that the TAS should prevent. In the case of TAS,

there is no exactly determined arrival time compared to the health care system. Accordingly, there is no precise control of demand over the existing supply in the form of handling equipment. A system with an exact arrival time has not yet been implemented, as traffic jams, accidents etc. would lead to strong fluctuations.

The approach of Open Access is mentioned to a minor extent in specialist literature. Due to the lack of detail in the publications, this offers great potential for improvement, especially in comparison to the health care system. One explanation for the predominant failure to comply with the Open Access approach may be a lack of interfaces between online platforms for booking time windows and the staff for manually entering same-day trucks. This only applies under the condition that personnel is made available for the appointment entry process or that manual interventions of this kind are possible.

The time windows often have a standard size per terminal. It is assumed that the truck arrivals deviate from the set time window value by a small standard deviation. As a safety factor, a buffer is inserted between individual truck handling operations, which can vary from terminal to terminal. As a result, time gaps between trucks are not used (Huynh and Walton, 2008).

4.3 Improvement Measures

In the following, suggestions are made for solutions which should serve to remedy the previously identified performance gaps. The proposed solutions are based on the presented approaches of time window booking systems in health care. In addition, these solutions are examined with regard to their adaptation and impact on TAS. Subsequently, an evaluation of the different solution proposals takes place.

4.3.1 Presentation of Measures

The performance gaps highlighted cannot be solved in isolation by the following proposed solutions. The elimination of a performance gap can at the same time lead to the reduction of further performance gaps. Subsequently, the three in section 3.2 presented approaches from the health care sector are transferred to TAS in ports.

Open Access

The Open Access is applied most easily in a hybrid form. This means that routine time window bookings can take place parallel to time window bookings made on the same day a few hours before container delivery or collection. In particular, smaller terminals that do not use a 24/7 working scheme are suitable for the Open Access approach. If, for example, a terminal is operated in a two-shift system, several time windows can be blocked proportionately for time-independent trucks. For larger terminals with a 24/7 working scheme, Open Access can be used in a modified form. Although there are no longer any extra blocked time windows, the approach is still suitable for closing unoccupied time windows. Trucks without appointments have the option of being assigned a corresponding time window on the same day. It is possible to make requests for free time slots throughout the day. With this procedure it is possible to fill free time windows caused by no-shows or rebookings.

Overbooking

Unnoticed time windows lead to a reduction in the performance potential of the terminals. The following solution for overbooking is first applied to fixed time windows and then to the assignment of time windows at flexible times.

The approach of fixed time window allocations can be further optimized for overbooking with a finer grid. This is done by overbooking the first available time slots of a day or a day segment. This counteracts the terminal resource idle caused by a missing queue or potential no-shows. In addition, the following time windows can be overbooked depending on the no-show probability. At the end of a day segment, no more overbooking of appointments should take place to avoid overtime of the workforce.

The enhancement provides for flexible assignment of time windows. Appointments or time windows can be assigned at any time. It is advisable to make overbookings without exception in the first time windows, as in the previous approach. For all other time windows, only one truck may be booked per time window. With regard to the length of check-in times, there will be a multiple coupling pattern resulting from the distribution of the actual check-in times of the trucks. The time windows that complete or end a day segment will be extended, as unexpected above-average handling times will be absorbed and overtime avoided.

Defragmentation

The current procedure is characterized by inefficiencies, as these tend to generate fragmentary time window sequences. Reasons for this are the allocation of time windows according to the preferences of trucking companies and/or the cancellation or change of previously allocated time windows. In the following, adaptations or modifications of the TAS management software are recommended. The goal is a minimal fragmentation in the sequence of all booked time windows. Each possible option of the time window selection is quantitatively evaluated with regard to the fragmentation effect. These evaluated time windows shall be proposed to the companies booking according to their possible impact on the status of the date fragmentation. A list of all available time windows contain date proposals that are found in the immediate vicinity of the desired date of the trucking company, but are sorted according to the effect on a defragmentation of the time window sequence. The first time window suggestions have the greatest effect on the defragmentation, while the last time window suggestions have the least effect. Trucking companies are encouraged, but not obliged, to accept the slots preferred by the terminal. The available time windows could be presented consecutively. Thus, the best time window from the terminal operator's point of view would be offered first. Only in case of rejection would the subsequent time window be shown.

4.3.2 Evaluation of Presented Measures

The presented measures are evaluated regarding the following criteria: Effort of introduction, impact on terminal productivity, influence on traffic jams in the port, effect on truck throughput time and influence on customer satisfaction. A multi-dimensional assessment of non-monetary variables is a good way of obtaining a multilayered and summarizing overall assessment. The evaluation of individual criteria is subsequently carried out with dimensionless evaluation numbers, which are then added up to a total evaluation number. The total valuation number ultimately represents the utility value. A ranking of the measures presented is created in Table 1 on the basis of the total valuation number. Four integer gradations from 0-3 are available for the valuation of these measures. These correspond to the scores 'poor', 'medium', 'good' and 'very good'. In order to enable the evaluation, the measures were compared on the basis of the publications found for each individual criterion. In particular, it was determined whether a measure was better or worse suited than the other measures to positively influence this criterion.

Table 1: Evaluation of selected measures

Criteria	Open Access	Over-booking (1)	Over-booking (2)	Defrag-men-tation
Implementation costs	2	2	0	1
Impact on terminal productivity	1	2	3	2
Influence on port congestion	1	1	1	1
Influence on truck turn time	1	1	1	1
Influence on customer satisfaction	2	1	1	1
Overall evaluation	**7**	**8**	**6**	**6**

According to the evaluation, the following picture emerges: The measure of overbooking dates (1) occupies first place with eight points. Second place went to the Open Access approach with seven points. In third place were the measures for overbooking appointments (2) and defragmentation, each with six points. However, it can be seen from the evaluation that the best-rated measure of overbooking appointments (1) does not represent the best possible solution in all individual parameters.

The characteristics of TAS differ due to a multitude of individual approaches and solutions in the implementation. For this reason and because of the insufficient literature situation, it is hardly possible to define starting points for which there is the possibility of connecting measures. It is recommended to first check the effectiveness of the measures by means of simulations and to adapt them to the existing system with the help of an iterative process.

5 Conclusions and Outlook

The aim of this study is to give a quantitative overview of a non-port time window booking system, to show their potentials and to examine the relevance of their systematic properties for TAS. Following a systematic literature research, the health care system turns out to be the best reference partner in terms of systemic characteristics. Subsequently, the benchmarking method is used to check the transferability of highlighted systemic characteristics of the health care system to TAS. In view of the task, an industry-independent process benchmarking is applied, which focuses on the TAS-critical processes of quota determination and time window booking. Subsequently, three measures from the health care sector are evaluated according to various criteria using a benefit analysis. The best overall result was achieved by overbooking appointments in fixed time windows, followed by Open Access, overbooking appointments in variable time windows and defragmentation.

The limiting factor to be taken into account in this study is that only one benchmark was carried out with the industry that had the most agreements with TAS in ports. Due to the high similarity of other areas, e.g. logistics, it is to be expected that potentially well transferable solutions can be generated there too, which were not examined here. Furthermore, the presented benefit analysis is based on a subjective evaluation. Other outcomes of the individual evaluations are therefore possible.

This study can be seen as a starting point for further research projects. In future, the improvement of TAS based on approaches of other industries should concentrate on further strategic and tactical aspects of the health care system. For an exact evaluation of the approaches, it might proof beneficial to use a simulation tailored to the terminal. This could help to eliminate individual weak points in the specific TAS.

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Cyber-Attack Impact Estimation for a Port

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Purpose: We investigate consequences of a cyber-attack on a port through a simulation model. Motivated by the impact of NotPetya on the container company A.P. Møller-Maersk and the entire supply chain we propose a method to estimate the consequences. Such estimation is a first step towards the identification of protection measures.

Methodology: We represent a port as a network of interdependent cyber and physical assets. The operational state of each component is measured on a 3-tier scale and may change due to external problems. The components reaction on security incidents is modeled using Mealy automata.

Findings: An implementation of the model as a network of coupled Mealy automata allows simulation of the dynamics after a security incident. This gives an overview on the expected condition of each component over time. The results can be visualized to identify parts that are particularly at danger.

Originality: The approach takes into account different kind of information on the cyber and physical system but also learns from past incidents. The automata simulation model provides estimate on the future behavior. Existing data may be used for validation.

Keywords: Cyber-attack, Cascading Effects, Port Security, Supply Chain

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1 Introduction

During the last years, critical infrastructures (CIs) have developed into complex and sensitive systems. Manifold dependencies exist between different CIs, leaving them vulnerable to failure in other systems and resulting reduced support in, e.g., electricity (Fletcher, 2001). At the same time, single CIs grow and become more heterogeneous. The probably most significant change during the last decade is the increasing digitalization that yields an interconnection between formerly separated physical and cyber systems. Physical processes are controlled through Industrial Control Systems (ICS), data is stored and analyzed and physical processes may be adapted due to this collected information (e.g., if a water supplier detects reduced quality of ground water, pumps may be switched off remotely). Not to the least, digitalization aims at increasing efficiency and simultaneously reducing costs.

Despite the many advantages of linking physical and cyber systems, this also paves the way for new threats. Recent incidents such as Stuxnet (Karnouskos, 2011), the hacking of the Ukrainian power provider in 2015 (E-ISAC, 2016) and 2016 (Condliffe, 2016) demonstrated impressively the potentially huge impact on CIs but also on society. Until 2017, the number of reported cyber incidents in the maritime sector has been relatively low (Verizon, 2017), despite some incidents as the hacking of the computer controlling containers enables drug traffic in Antwerp (Bateman, 2013). In the aftermath of the impact of NotPety on A.P. Møller-Maersk (Greenerg, 2018), awareness has risen. When the COSCO Shipping Line was hit by a cyber-attack in July 2018, it affected the organization network but business operation was still possible (World Maritime News, 2018). Later the same year, the

ports of Barcelona and San Diego reported on cyber-attacks (Cimpanu, 2018b). Malware attacks such as WannaCry and NotPetya (both in 2017) also affected the maritime sector.
In this article, we take a hybrid view on nowadays complex CIs through the concept of hybrid situational awareness. Based on this model we investigate consequences of a cyber-attack on the overall system. Motivated by the consequences of NotPetya, we illustrate the approach by investigating the impact of such an attack on a port.

2 Hybrid View on Critical Infrastructures

The way most CIs have developed over the past years results in a big system consisting of two interconnected subsystems, namely the physical and the cyber system. Information on the individual systems is available but typically not combined to understand the behavior of the overall system. The knowledge about the subsystems is often called Physical Situational Awareness (PSA) and Cyber Situational Awareness (CSA), respectively. People may have domain expertise in either the physical or the cyber domain, but hardly both. However, it is exactly the cross impact that bears high risks, and limited view on only cyber or physical domains may lead to a failure of the overall security policy. The issue that a good risk model needs to tackle is bridging isolated expertise and views. This requires a unifying model describing both cyber and physical assets in the same terms, so that the two are compatible for a joint simulation model. The knowledge about the overall system is termed Hybrid Situational Awareness (HSA) and extends PSA and CSA by explicitly taking into account interdependencies. As in (Schauer et al., 2018), we divide the HSA in two components: a module

focusing on detection of suspicious correlation of events (called the correlation engine) and another module focusing on the consequences of an incident in this hybrid setting (called the propagation engine).
In Section 2.2, we propose a simulation model of error propagation in such a hybrid system. In essence, the model is a network of interconnected Mealy automata, where the "automata" describes the individual evolution of an asset, and it is "Mealy" to account for asset interdependencies, using domain-specific common vocabulary between distinct domain experts. In Section 2.3, we sketch an implementation of the model that we use in the remainder of the paper.

2.1 Existing Approaches

Various approaches exist to model cascading failures in a network. Classical network models working with topological properties (Wang and Chen, 2008; Holme, 2002; Motter et al., 2002) are generally applicable but at the same time are not able to take into account domain characteristics which makes them error-prone when it comes to predictions. Recent approaches work with networks of networks or interconnected networks (Buldyrev et al., 2010) and show that these behave different than single networks. The high complexity of cyber-physical networks makes it impossible to perfectly predict future behavior, yielding an increasing number of stochastic models. These include advanced Markov chain models (Wu and Chu, 2017; Wang, Scaglione and Thomas, 2012; Rahnamay-Naeini and Hayat, 2016), branching process models (Dobson, Kim and Wierzbicki, 2010; Qi, Sun and Mei, 2015; Qi, Ju and Sun, 2016) and other high-level stochastic models (Dong and Cui, 2016). While the probabilistic nature of cascading failures is essential (and thus incorporated in our model), we prefer an event-driven model through automata.

In the context of port security, different approaches on security exist (Andritsos and Mosconi, 2010; Andritsos, 2013) but focus mostly on physical security. An approach towards harmonization of cyber and physical components is presented in (Papastergiou and Polemi, 2014) but models of how to combine information from both sources are currently missing.

2.2 Simulation-Based Approach

The simulation-based approach proposed in (König et al., 2019) models a critical infrastructure as a directed graph $G = (V, E)$, where each vertex $v \in V$ corresponds to an asset of the CI and edges represent dependencies of one asset on other one. Each asset individually maintains a "state of health" that changes over time, either directly upon an incident or indirectly by notifications of state changes received from other assets. Figure 1 shows the overall model (left) with internal models specific for each CI (right). We assume that the state of health is measured on a three-tier scale, ranging from "functional" (normal working condition) to "affected" (impaired functionality but the asset still works to some extent) up to "outage" (temporary or permanent breakdown). Any such change of state of an asset is communicated (as notifications) to other assets, which in turn may, but not need to, change their states accordingly. Hence, an asset will react on incoming signals from other assets and itself emit notifications to dependent assets. The natural model to capture such behavior is a probabilistic Mealy automaton, in which a state transition is triggered by an incoming symbol α (signal) and may cause an output symbol (outgoing notification β), but only so with a

probability p (or $p = 1$ if the transition is deterministic). The simulation itself then starts with an initial signal that is the incident, which goes to all assets, respectively representing
Mealy-automata, directly affected by the incident. Their state transitions and according outgoing signals to other dependent assets then trigger further cascading effects in other assets and so on.

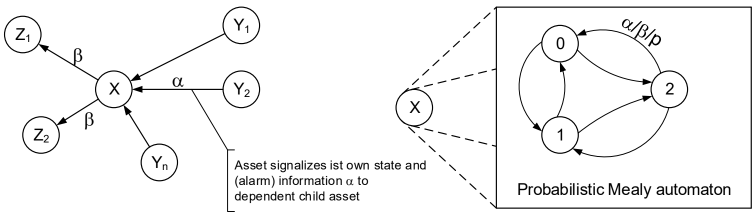

Figure 1: Dependency structure (left) and inner model (right)

A bit more formal, the infrastructure model is a directed graph where each node representing an asset is a probabilistic Mealy automaton

$$M = (S, \Sigma, \Sigma, \delta, \lambda, s) \quad (1)$$

where S denotes the set of all states an asset can be in, Σ is the input and output alphabet (assumed to be equal here, but this can be generalized), δ a transition relation, λ an output function and $s \in S$ the initial state. Since transitions happen only with a certain probability, δ assigns a probability distribution to each pair of state and input symbol.
Before we show how the model helps estimating the impact of a cyber-attack on a port, we give an overview on the implementation in the next section, including some remarks on how to specify the model parameters.

2.3 Remarks on Implementation

Overall, the considered spreading process is an event-based discrete time simulation, implementable in tools like OmNet++, ns-3 or others. Our research prototype (Schauer et al., submitted) is a designated implementation of the mechanisms described above. It allows the user to draw and connect the important physical and cyber assets on a web application while the actual simulation is done in an application programming interface (API). The prototype provides two main outputs: first, a distribution of the final state for each asset and second an overview on which assets are affected after a fixed time interval.

While the implementation of a system of coupled probabilistic Mealy automata is not technically difficult, the model comes with a large number of parameters that need to be specified. Each transition within each Mealy automaton (asset) has an incoming alarm, an outgoing notification and a probability of occurrence. We treat this problem with a machine-aided parameterization method, which we sketch below.

It is useful to assume that all assets share the same state space and to fix a common set of incident notifications Σ exchanged between assets (at least for reasons of understandability between the assets, since a dependent asset should “understand” what its parent node notifies it about). The elements of Σ can be arbitrary structures, and we assume those to be string-encodings of alert messages, containing (among others) at least a timestamp, criticality level and impact information for the notifying asset. This information can then be processed by the receiving asset to update its own state based on the current one (the function $\delta: \Delta(S \times \Sigma) \to S$), and update other assets accordingly (function $\lambda: S \times \Sigma \to \Sigma$). The symbol Δ here denotes the simplex taken over all triples in $S \times \Sigma \times S$, corresponding to the probabilities that a transition happens. In the specification, this amounts to ascribing a value p to the state transition from $s_1 \to s_2 = \delta(s_1, \alpha)$ upon input symbol α and output symbol $\beta = \lambda(s_1, \alpha)$, thus describing the transition as a triple $\alpha/\beta/p$ (cf. right hand side of Figure 1). The terms α and β are alert or status notification strings that assets can exchange, and whose specification depends on the application context. As such, specification may be in a common syntax to capture all sorts of relevant information; a laborious and complex, yet not technically difficult, task. Estimating the probabilities p is a different story: we propose computing these values from example instances of transitions $s_1 \to s_2$ with labels α/β and transition flags 0/1 labeled by experts to indicate when a transition would occur (under the conditions α and from the state s_1) or when it would not occur. Given many such examples, we can step forward by fitting a logistic regression model to this training data and compute (predict) the values p for any transition using that model.

3 Consequences of a Cyber-Attack on a Port

For the upcoming analysis, we consider a fictitious European port as an example CI since ports are crucial for supply and trade and limited functionality significantly affects society. In course of the ongoing digitalization, the integration of information and communication technology (ICT) systems became more and more important for ports for automation as well as control purposes. As for any other infrastructure, this paves the way for sophisticated attacks, ranging from ransomware attacks (Georgia Institute of Technology, 2017) to advanced persistent threats (Tankard, 2011).

In response to these threats, new regulations and standards have been developed, such as the Interim Guidelines on Maritime Cyber Risk Management by the International Maritime Organization (IMO) in 2016 (IMO, 2016). The ISO 28001 standard (International Organization for Standardization, 2007) focuses on the overall security of supply chains and explicitly takes into account the interaction between all involved partners. Although some approaches have been defined to assess cyber threats in maritime supply chains (Kotzanikolaou, Theoharidou and Gritzalis, 2013; Polemi and Kotzanikolaou, 2015; Schauer, Polemi and Mouratidis, 2018), a holistic view taking into account both cyber and physical information seems to be missing so far. Such a holistic view is necessary to understand consequences of a cyber-attack, which in turn is a core duty in risk management. In the remainder of this section, we consider a fictitious cyber-attack and investigate its effect on a port.

3.1 Scenario Description

While the considered cyber-attack is purely artificial, it is inspired by reports on NotPetya (Countercept, 2017) and aims at illustrating potential consequences of such an incident. Thus, it inherits some major characteristics of NotPetya while it does not intent to reconstruct the event. NotPetya started with a compromised update of the MEDoc accounting software and spread like a worm to other machines and organizations. Different from WannaCry, NotPetya did not spread over the internet, but through interconnected networks using stolen credentials form infected machines (Countercept, 2017). This way, it also affected Windows computers that were fully patched and not using the MEDoc software. NotPetya used two encryption mechanisms: one that only encrypts files of a certain type and one that encrypts the Master File Table (MFT) that allows reading files from the hard drive (Countercept, 2017). Encryption of the MFT is possible by modification of the Master Boot Record (MBR) that controls the system start. If both the MFT and the MBR are encrypted, all data is lost. If only the MFT is encrypted but not (yet) the MBR, it is possible to recover some data (Countercept, 2017).

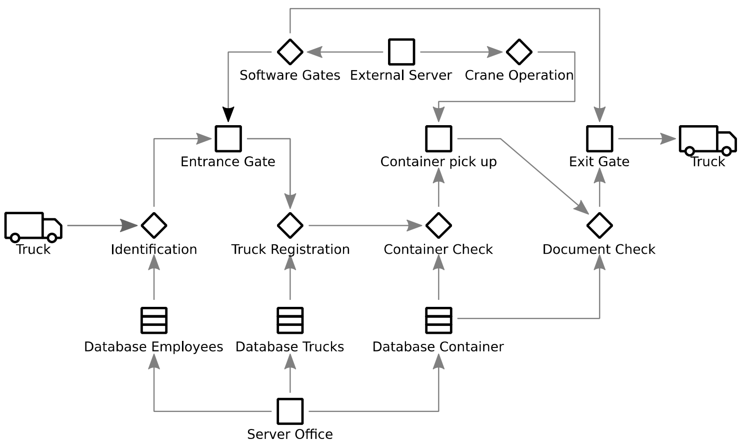

Figure 2: Important components for container pick up

In order to keep the procedures and the results comprehensible, we do not model the entire port but only consider a truck picking up a container at the port for further distribution. The steps of this business process are as shown in Figure 2 where besides special icons for trucks and databases squares are used to represent physical assets and diamonds represent software supported processes. When the truck arrives at the port, the driver is required to identify as an employee who is authorized to enter the area. After passing the entrance gate (and potentially a security scanner ensuring it does not carry dangerous goods), a formal check of the truck follows, i.e., if it is on the list of registered and approved trucks. Next, all information about the requested container is checked: does the driver have permission to pick it up and is the container available (off the ship and cleared customs)? All these checks rely on databases about personal, trucks and container, respectively. After successful registration, the driver receives a printed barcode containing the information on where to pick up the container, i.e., where to park so that the crane can load the container on the truck. Once the container is on the truck, its barcode is checked (if necessary, also other characteristics such as temperature). Finally, all documents are checked at the exit gates and the driver is authorized to leave the port. Operation of both the gates and the cranes is governed by software provided by an external partner, such as Maersk.

3.2 Impact Simulation

Simulation of an attack according to the proposed method is done with the tool described in Section 2.3 (we use the online version (AIT, 2019) for visualization). The state of an asset is measured on a 3-tier scale to represent the impact due to the attack in terms of data loss (depending on the encryption mechanism, as described in Section 3.1) or to represent functionality. In both cases, higher numerical values indicate more severe problems.

If a cyber-attack hits the office network, it causes failure of all connected PCs and laptops, compromising databases and customer data. Other components such as gates or cranes depend on servers and software provided by partners and are thus more affected if a partner is victim of a cyber-attack.

We consider two different scenarios:

1. The case where a cyber-attack hits the ports own network (starting at the node server office)
2. The case where the external provider is hit (starting at the node external server)

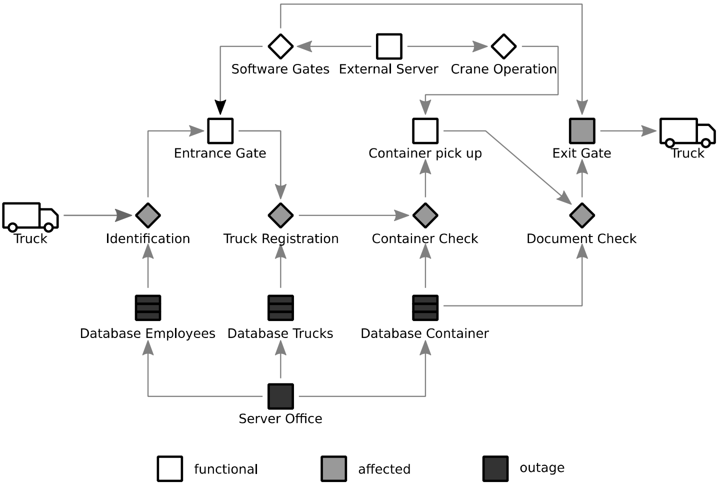

Figure 3: Consequences of a cyber-attack on the office network

In the first case, this will cause loss of information stored in the different databases, which in turn affects the corresponding checks. Most of this work can be done manually, so that the entire process slows down significantly but operation should still be possible. Potential consequences are illustrated in Figure 3. The exit gate is not facing operational problems but due to the delays along the line it is not able to provide the optimal service (e.g., further checks may be necessary before a truck may leave the ports premises).

In the second case, the cyber-attack directly affects functionality of the gates as well as the cranes that allow picking up a container. This virtually interrupts transportation to and from the port, as shown in Figure 4. The color codes in the picture (black, grey, white) directly correspond to the states (failure, affected, working), thus providing an immediate visual guidance of which parts are affected to which degree. Theoretically, this relates our work to percolation, which asks for the evolution of large clusters within a graph; in our case, the question would be about the potential rise of a giant red area within our network, expressing a large-scale impact from an attack. We do not explore this theoretical route any further here, and leave it as subject of future considerations.

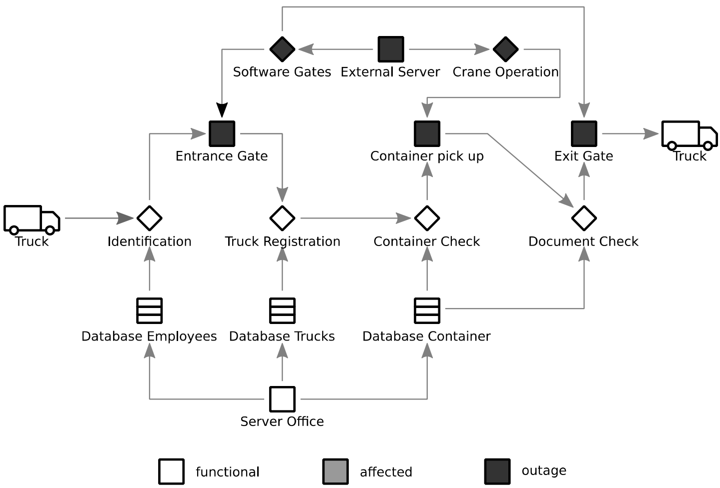

Figure 4: Consequences of a cyber-attack on the external network

A comparison of the two examples illustrates that a port may be even more sensitive to disruptions of services provided by external partners than to direct (targeted) attacks to the port itself. This illustration works with single simulations of each scenario but the tool used allows for iterated simulation to allow statistical inference on the results.

3.3 Comparison with Reported Impact

Many companies were affected by NotPetya, e.g., the pharmaceutical company Merck, FedEx's subsidiary TNT Express, the food producer Mondelez or the manufacturer Reckitt Benckiser (Greenerg, 2018). The effect it had on A.P. Møller-Maersk (that used MEDoc in an office in Odessa) is of particular interest since it affected the entire (cargo) supply chain and in particular numerous ports all over the world, e.g. India's largest container port (PTI, 2017), demonstrating the sensitivity of (maritime) supply chains.
The impact of NotPetya can only be estimated from public reports. A.P. Møller-Maersk stated at the Davos World Economic Forum in 2018 that it had to reinstall 45,000 PCs and 4,000 servers but recovered in less than two weeks (Cimpanu, 2018a). Despite a huge amount of manual work and immense effort to find an intact backup, the damage is estimated between $250 and $300 million. Not only were basically all computers of Maersk's 176aramet. 80,000 employees frozen and the booking website down, also terminals' software was affected. Designed for data exchange, the interconnection between the two networks caused many troubles. In 17 out of the 76 Maersk's terminals, gates were out of order and containers could neither be picked up nor dropped off (Greenerg, 2018).

4 Conclusion

Reported cyber incents like NotPetya and others demonstrate the strong mutual dependence of infrastructures on one another. The particular nature of advanced persistent threats to exploit a diverse spectrum of platforms and media for an attack calls for descriptive models capable of equal flexibility and diversity. We propose probabilistic Mealy automata for a generic description of the dynamics of the interplay of systems inside a CI. For a comprehensive picture about the risk of cascading effects, a simulation model necessarily needs to unite different domains, and this is a project of joint maintenance between CI providers. Given the interconnectedness of infrastructures, it is no longer sufficient to secure one's own domain, since an attack occurring at the "neighbor's site" may indirectly affect us as much (or even more) as a direct hit by an attacker. Understanding cascading effects thus appears as crucial for contemporary and future system security.

The scenarios depicted in this work have been inspired by reports about NotPetya and its relatives (precursors and successors), and compiled into a software prototype for probabilistic simulation of possible scenarios. A large entirety of these then converges into a picture about what could happen, what is likely and which parts are unlikely to be affected by certain scenarios. While a probabilistic simulation cannot deliver guarantees for the prediction, it helps prioritizing security mitigation actions and points out spots that are more vulnerable than others (and hence need quicker attention).

Future work along these lines will go deeper into the parameterization of the model in the sense of "training" it based on domain expertise (expert risk assessments or data from reported incidents).

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Modeling Autonomously Controlled Automobile Terminal Processes

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Purpose: Automobile terminals play an essential role in automotive supply chains. Due to short planning cycles and volatile planning information, the yard assignment determines terminals performance. Existing planning approaches are not able to cope with these dynamics. This contribution proposes a novel bio-analogue autonomous control method to face these dynamics, its effects and to improve the terminals performance.

Methodology: Causes of internal and external terminals dynamics will be discussed and an autonomous control method will be derived. A generic 185arameterizable automobile terminal model and its implementation to a discrete event simulation will be introduced in this paper. This simulation is used to compare the new approach to classical yard assignment.

Findings: This paper contributes to the theoretical understanding of causes and effects of dynamics in the context of automobile terminals. It will show that autonomous control outperforms classical approaches under highly dynamic conditions.

Originality: The generic modelling approach is a novel description of automobile terminals. It allows investigations of a broad spectrum of use cases. Moreover, the bio-analogue autonomous control for automobile terminals is an innovative approach

Keywords: Automobile Logistics, Port Terminal, Autonomous Control, Discrete Event Simulation

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1 Introduction

During the recent years, the shipment volume of finished cars increased constantly, due to an emerging global interconnection between production and distribution networks. In this context, automobile terminals are central elements in international automotive supply chains. Automobile terminals allow the transshipment from the production plant to the target markets. Besides handling of finished cars from different transport modes (e.g., ship or truck), these terminals usually offer a broad spectrum of additional technical services in order to meet customers' demands in the port of destination. In general, the main tasks of automobile terminals can be defined as handling, technical treatment and storage of finished vehicles (Mattfeld, 2006; Böse and Piotrowski, 2009). All related processes are triggered directly by the car manufacturers (OEM). Accordingly, automobile terminals can be interpreted as a classical decoupling point in the automotive supply chain, which allows to react flexibly to demand fluctuations (Dias, Calado and Mendonça, 2010). Hence, planning of processes automobile terminals is faced with forecast-driven and customer-order driven processes at the same time. This strongly affects the yard master planning, which aims at minimizing the distance between the point of car entrance, storage area and its exit point (Görges and Freitag, 2019). Classical master planning approaches solve this task by assigning predefined parking areas to the different vehicle types (e.g. sorted by manufacturer, model and destination). This leads to good planning results for situations with high forecast quality and less dynamics. However, due to its long term orientation, this type of yard

master planning is prone to forecast deviations, volatile parameter variations and unforeseen events, which may affect the terminals performance negatively (Cordeau et al., 2011; Mattfeld and Orth, 2006).
Autonomous control of logistics processes address these shortcomings by transferring decision making capabilities from a centralized planning instance to the logistics object itself. Due to interactions and decision making of intelligent logistics objects, autonomous control aims at creating self-organizing systems behavior, which increases the systems performance (Windt and Hülsmann, 2007). This self-organization can be seen as emergent behavior of a complex dynamic system, which is not a characteristic of the systems elements but of the total system (Vaario and Ueda, 1998). For production logistics, different autonomous control strategies showed already their operational potential. In the context of automobile terminals, first implementations indicated promising results concerning the assignment of cars in import processes to technical service stations (Böse and Piotrowski, 2009). However, comprehensive autonomous control strategies covering all inbound and outbound material flows of an automobile terminal are still missing. Thus, this paper will focus a broader use case. It will derive an autonomous control strategy, which allows the integration all flows of cars (import, export and inter terminal) at an automobile terminal. In order to analyze the performance of the autonomous control strategy, this paper will present a generic modeling approach for investigating a broad range of related scenarios. Furthermore, it will introduce a discrete event simulation model implementation for analyzing these scenarios. This simulation model will be used to investigate the performance of the derived autonomous control method compared to a classical yard master plan.

2 Autonomous Control of Automobile Terminals

2.1 Terminal Planning

Material flows in automobile terminals can be characterized as a sequence of several generic sub processes (e.g. loading or storage operations). Basically, every process starts with unloading operations from different transport carriers (truck, rail, ship) followed by the storage of the vehicle. Subsequently, cars are loaded to outbound transport carriers or receive one or more technical services. Automobile terminals offer a broad spectrum of technical services with highly varying process times (Hoff-Hoffmeyer-Zlotnik et al., 2017). Figure 1 depicts this physical material flow of vehicles at an automobile terminal. Furthermore, it shows the related planning tasks in respect to their temporal occurrence (planning horizon). The overall objective of all planning tasks is the efficient operation of all physical vehicle movements from the source (i.e. unloading point at the terminal) to the sink (i.e. loading point)(Özkan, Nas and Güler, 2016). On a strategic level, planning focuses on long term decisions like the planning of infrastructure (e.g. additional berth or yard extensions). Forecasting of expected vehicle volumes and related long-term planning of resources belong to this strategic time horizon as well. Based on these forecasts, a long term orientated area master planning derives required parking areas (Mattfeld, 2006). A result of this planning step is a rough assignment of estimated vehicle volumes to parking areas. This first assignment is the starting point for the tasks on the tactical planning horizon. In this planning phase, forecasted vehicle volumes are used to plan berths and the utilizations of berths (Dias, Calado and Mendonça, 2010). Usually, forecasts become more precise and get a higher level of detail with more specific information (e.g. model-destination split or volume related model-split). The results of the strategic planning is used in the tactical planning to generate and adjust the yard plan. The yard plan comprises the assignment of vehicle volumes to specific areas of the yard. In order to generate short routes between the loading and unloading locations, the yard planning often includes the localization of loading and unloading operations (berth allocation planning, storage space partitioning and storage area design) (Mattfeld, 2006; Mattfeld and Orth, 2006). The personnel requirement can be derived with the results of localization and vehicle assignment. In general, the operational planning is characterized by increasing level of relevant information (e.g. ETA of ships or the assignment of cars to ships). On this operational planning level, the results of tactical planning are refined in predefined turns or with a rolling time horizon (Mattfeld and Kopfer, 2003). This approach allows to react to changes and external disturbances (e.g. delay of ships or changes in ships transport quantities).

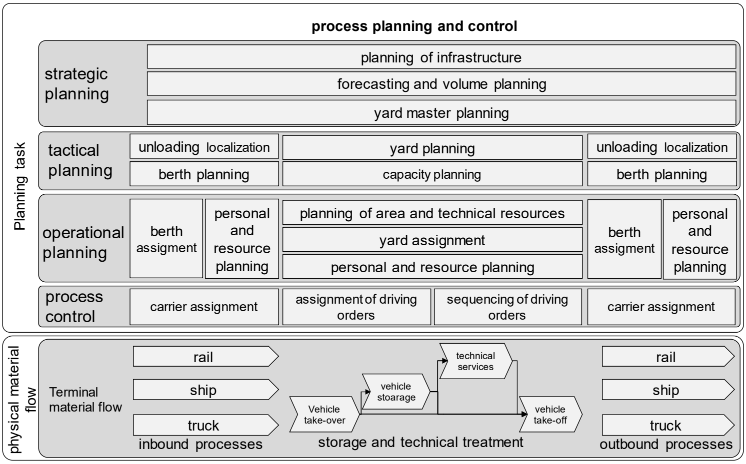

Figure 1: terminals planning task – based on (Görges and Freitag, 2019)

These plan adjustments may lead to changes of routes length between inbound locations, storage areas and outbound locations and affect the overall terminals productivity and the personal requirements. The process control focuses on the execution of particular driving orders resulting from the previous planning tasks. It assigns driving orders to workers and monitors the progress of order processing

Yard planning plays a key role in the described, cascaded planning process. It mainly determines driving distances between cars' arrival and departure points and the related process productivity (i.e. cars per hour per worker). Incoming vehicles are sorted and assigned to parking lots according to the yard master plan. At the arrival of a vehicle, usually the information about its outgoing transport carrier is not available. Later, the customer (e.g. OEM) sends advices for particular cars, assigning them, for example, to a specific ship. Dias et al. (2010) describe this characteristic as parallel push and pull processes occurring at the same time at an automobile terminal (Dias, Calado and Mendonça, 2010). These parallel push and pull processes allow terminals to react quickly to changing demands in the supply chain. However, this also leads to complex internal dynamics in the terminals processes and short planning time horizons. Classical yard planning addresses the orders' neutral (forecast-driven) aspect. Volumes of vehicles are assigned to specific parking areas of the terminal based on forecasts. After customer orders are available, the operational planning (e.g., berth planning) aims at increasing the terminals productivity by reducing distances between storage area of the cars and the outgoing transport carrier (e.g., by assigning ships to quay positions). Figure 2 depicts both push and pull processes of automobile terminals and relates them to the planning tasks. In this context, terminals offer a higher degree of flexibility to the entire supply chain at expense of an increasing complexity of the terminals' planning and its operative process execution. In this context, the yard planning is a key instrument to cope with forecasted vehicle volumes and to allocate it to parking areas.

Accordingly, it determines routes of vehicles from the source to the sink on the terminal. Due to the order-natural nature of the arrival process, the yard planning cannot react to near-term changes (e.g., increasing or decreasing vehicle volumes). An increasing degree of flexibility and dynamical adjustment of yard assignments may increase the terminals' performance (Görges and Freitag, 2019).

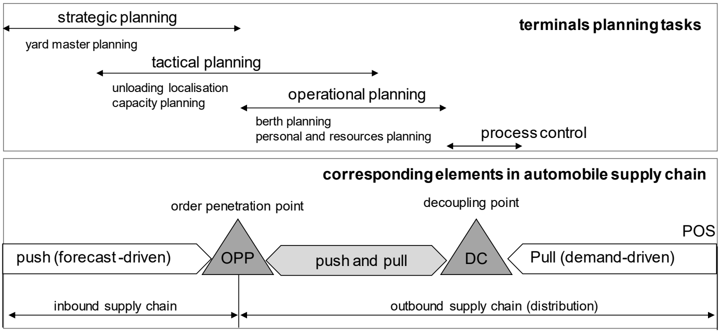

Figure 2: terminal planning in the context of automobile supply chains based on (Dias, Calado and Mendonça, 2010)

2.2 Concept of Autonomous Control

The concept of autonomous control offers a novel approach to cope with dynamics in logistic systems. It aims at transferring decision making capabilities from a centralized planning instance to the logistics object (e.g., goods or machines). By enabling decentralized decision making, autonomous control intends to create an emergent systems behavior which allows to deal with dynamics and increases the systems performance. Autonomous control is not limited to specific types of logistics systems. There are different approaches for production logistics (Toshniwal et al., 2011), for transport logistics (Rekersbrink, Makuschewitz and Scholz-Reiter, 2009) and for aspects of terminal logistics (Böse and Piotrowski, 2009), by implementing local decentralized decision making capabilities. Wind and Hülsmann (2007) introduced the term intelligent logistics object. Intelligent logistics objects cover both, physical real world objects (e.g., vehicles on a terminal) and immaterial objects like customer orders. By using modern communication technologies, intelligent logistics objects are capable to exchange and collect information about relevant system states (Windt and Hülsmann, 2007). Existing autonomous control methods can be classified as local information methods and information discovery methods. Local information methods collect and process only local system information. They can be further classified as rational, bounded rational and combined decision strategies (Scholz-Reiter, Rekersbrink and Görges, 2010). Rational methods use performance measures like estimated throughput times, inventory or route distances for decision making. Bounded rational strategies try to adapt complex decision patterns from other systems. Often these strategies are inspired by biologic systems phenomena (e.g., foraging behavior of insects or bacteria). A combined strategy is based on bounded rational decision mechanism and adds rational aspects (e.g. for a better implementation of restrictions).

By contrast, information discovery methods receive relevant information from interactions with other logistics objects. In this context the requested information can be passed along several logistics objects. Usually these information request do not cover the entire system, but is directed to relevant local information. Existing information discovery methods are inspired by technical protocols for communication networks and transfer routing mechanisms from these protocols to autonomous decision making of logistics objects (Rekersbrink, Makuschewitz and Scholz-Reiter, 2009). Due to their complexity, information discovery methods are designed for specific logistics scenarios (vehicle routing or flexible flow shop scenarios) and cannot be easily transferred to other system types like automobile terminals.

First approaches of integrating autonomous control to automobile terminals showed already promising results. Böse and Piotrowski (2009) present a rational decision strategy for assigning cars to storage areas for technical treatment, which increases the handling performance (Böse and Piotrowski, 2009). However, this approach addresses specific sub processes of the import process and neglects cars arrival and departure points (e.g., berths). In order to design a comprehensive autonomous control strategy covering all processes of automobile terminals, a systematic approach is necessary. A procedure model for designing autonomous controlled automobile terminal processes is presented in (Görges and Freitag, 2019). In a first step a general target system has to be defined, which fits to the planning tasks and results described in section 2. In this respect, the total driving distance of vehicles (from the source to the sink) is a suitable and simple measure to analyze the methods performance. Subsequently, potential logistics objects for autonomous decision making have to be identified. In order to align the autonomous control strategy with terminals planning tasks, potential logistics objects should be the subjects of planning. In the case of automobile terminals, potential objects are: vehicles, vessels, trains and trucks. As a starting point this paper presents an autonomous control method for yard assignment of vehicles. This method considers status information of vessels, trains and trucks and allows autonomous decision making of vehicles choosing a parking row.

3 Generic Automobile Terminal Model

3.1 Structure of the Generic Scenario

In order to derive and analyze methods for an autonomous yard assignment, this paper proposes a generic automobile terminal model. This generic scenario is organized on two hierarchical layers. On the top layer it consists of nxm adjustable parking areas (A_{11} to A_{nm}). Cars arrive at the terminal via sources (I_1 to I_k) and leave the termial system via sinks (O_1 to O_j). Figure 3 depicts the structure of this generic scenario. Sources and sinks may be modelled as incoming (or outgoing) trucks, trains or ships. All parking areas are surrounded by driveways allowing cars to get from a parking area to another (or to a sink).

The second layer describes the parking area and its properties. A parking area is defined by its height (h), is width (w), and the row width (r). The number of parking rows (R_1 to R_l) results of these parameters. The orientation of rows is perpendicular to width dimension (see Figure 3). The row capacity is defined by h divided by the length of cars. The capacity of a parking area is defined by the sum of all rows' capacity.

This generic structure is the basis for the specific scenario investigated in this paper. In order to keep the scenario as simple as possible, a setting of 4x4 storage areas is used. The area width is $w = 160m$, the area hight is $h = 75m$ and the row with is $r = 3m$ for each storage area. According to these parameters the terminals capacity is 12720 cars with a standard length of 5m.

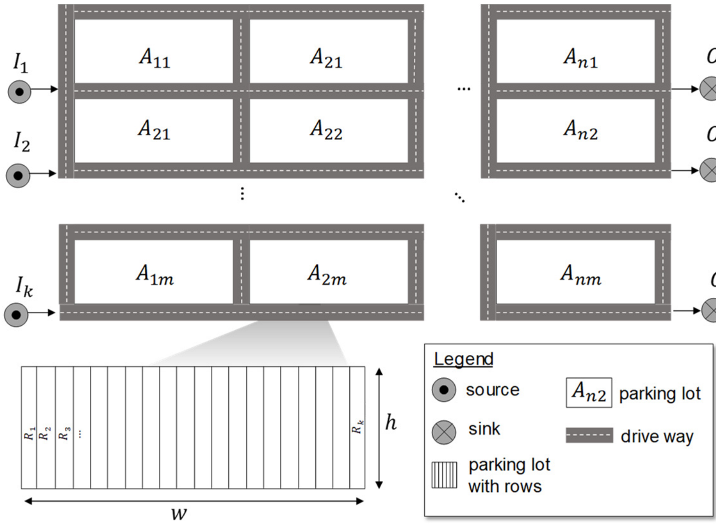

Figure 3: generic automobile terminal scenario

3.2 Modeling In- and Outbound Dynamics

The following section describes the general test settings used to parameterize inbound and outbound processes of cars. In this scenario two OEMs deliver their vehicles for export to the terminal by rail. Each OEM delivers two model types for two different destinations. A combination of OEM, model type and destination is defined as a category k of vehicles. The arriving volume of vehicles of a category k is defined by a sine function. This allows to model volatile seasonal demand fluctuations. Similar seasonal effects can be observed in arrival volumes of real automobile terminals. Equation (1) shows this function and its parameters. $I^k(t)$ is the incoming volume at day t. The mean arrival rate of vehicles is defined by λ^k. The amplitude of the sine function is defined by μ^k. In order to avoid negative arrival volumes the amplitude has to be smaller than the mean arrival rate ($\mu^k \leq \lambda^k$) . Besides the mean arrival rate, the phase shift φ^k and the period T determine the dynamic characteristics of this arrival function.

$$I^k(t) = \lambda^k + \mu^k \cdot \sin(\frac{t}{\mathrm{T}} + \varphi^k) \tag{1}$$

The following Table 1 shows the four categories of cars used in this scenario and the corresponding arrival parameters. It presents the values for λ^k for the particular implementation used in this paper.

Table 4: OEM's model and destination mix

OEMs	**Model**	**Destination**	**Mean arrival rate (λ) [car/d]**	**Initial Inventory**	**Phase shift**
OEM 1	M1	D1	100	1000	0%
OEM 1	M2	D2	75	1000	25%
OEM 2	M3	D1	100	1000	50%
OEM 2	M4	D2	75	1000	75%

In order to generate a realistic systems behavior, the terminals initial inventory has been set for every category to 1000 vehicles. The phase shift has been modeled in steps of 25% (related to the period of 365 days) for each category. The period T has be set to a quarter year. Figure 4 shows the sinusoidal inputs for all categories and the total input. The upper graph of Figure 4 depicts exemplarily the input volumes of OEM 1 model M1 and OEM 2 model M3.

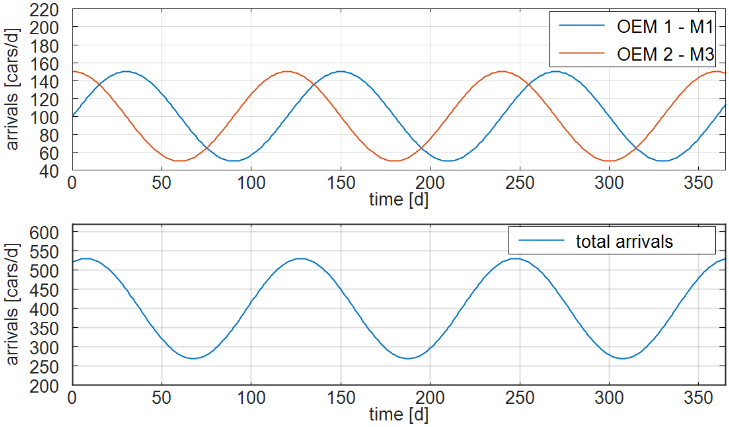

Figure 4: arrivals of OEM 1 & OEM2 (top); total arrivals (bottom)

Table 2: inventory times

	OEM 1 - M1	**OEM 1 - M2**	**OEM 2 - M3**	**OEM 2 - M4**
avg. inventory time [d]	10	20	10	20
variance [d]	2	2	2	2

The departure of vehicles is modelled in two different variants. The first variant uses simple constant inventory times modelled by adding a normal distributed delay to the arrival time of each vehicle. Accordingly, cars leave the terminal after a predefined time. Table 2 summarizes the underlying departure rates.

The second variant models the departure of cars in a more realistic way. In this variant ships sailing to destination D1 and D2 are generated as a time series with a normal distributed shipment volume per vessel.

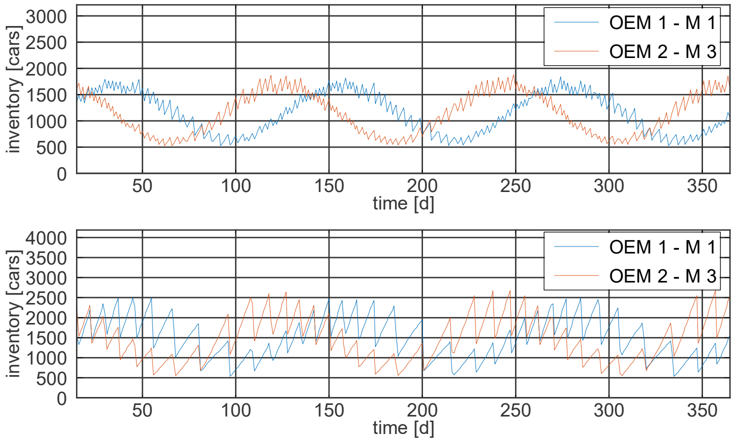

Figure 5: inventory over time: avg. 600 cars per ship (top); avg. 2000 cars per ship (bottom) for bulked departures

The ships arriving at the terminal have an average capacity based on a normal distribution. This leads to a bulked departure of cars over time. In this scenario, the average ships' capacity *s* will be varied from 500 to 2000 with a standard deviation of 10% of the mean value. Figure 5 shows the estimated inventory over time for different mean ships capacities. It shows that the mean ships parameter *s* has an impact on the dynamic of the inventory time series. Comparable inventory curves can be observed in real automobile terminals. This scenario comprises according to the sinusoidal inputs, the initial terminals inventory and the output rates (see Table 1 and Table

2) approximately 127.000 vehicles running through this scenario in 365 days.

In the 4x4 scaled scenario there are three sources and three sinks. The locations of sources and sinks will be addressed in detail in section 4.1 (Figure 6 summarizes their locations). The split of outgoing volumes of both OEMs is modelled as follows: At source 1 75% of OEM 1's volume arrive. At source 2 25% of OEM 1's and 25 % of OEM 2's volumes arrive and at source 3 75% of OEM 2's volume arrives. 75% of all ships sailing to destination 1 leave from sink 1, 20% from sink 2 and 5% from sink 3. For destination 2 75% leave from sink 3, 20% from sink 2 and 5% from sink 1.

4 Yard Assignment Methods

4.1 Conventional Yard Assignment

Based on these information a simple planning and assignment of cars to parking areas has been done. Figure 6 shows these assignments. The main concern of this assignment is to generate short routes between sources, storage areas and sinks. For example most cars of OEM 1 will arrive at source 1 and leave at all sinks. Thus, the assignments are close to source 1. Usually, different models from one OEM may be mixed when the terminals utilization is high. Thus, Figure 6 shows the primary assignment of cars and a secondary assignment in brackets. The secondary assignment can only be used if no free row of the primary assignment is available. These assignments are considered as results of a classical planning process in the following evaluation.

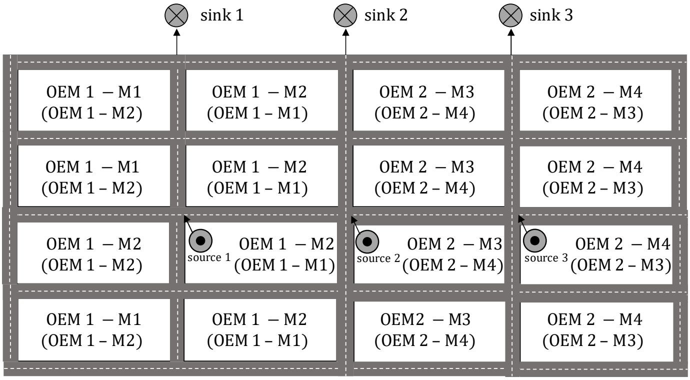

Figure 6: classical yard assignment

For the purpose of benchmarking a randomized assignment will also be used. In this case arriving cars are assigned to a randomly chosen row on the terminal. Only capacity restrictions of a row have to be met.

4.2 Pheromone Based Autonomous Control Approach

The autonomous control method presented in this section allows cars to evaluate, to compare and to choose a parking row by a pheromone based approach, which is inspired by ant's natural foraging behavior. As depicted earlier, bounded rational strategies like this offer the possibility to consider many different decision parameters. The method at hand can be seen as a combined method, using bounded rational aspects and rational measures. Pheromone based approaches have shown their capability to react on dynamical changes and to stabilize the systems behavior under volatile conditions (Windt et al., 2010). Accordingly, this approach seems to be suitable to the vehicles yard assignment at an automobile terminal. In general phenome based methods imitate communication principles of social insects (i.e. ants). While searching for food, ants leave evaporating pheromone trails, marking possible routes to food sources. Other ants are attracted by these trails and follow it. Ants following a trail increase the pheromone concentration. The pheromone concentration decreases in time due to the natural evaporation process. By using this interplay between marking trails with pheromones on the one hand and natural evaporation process on the other hand, ants are able to find the shortest routes to food sources. Autonomous control methods using this principle leave relevant information in the system (e.g. throughput times) as an artificial pheromone. Subsequent objects are able to read this pheromone information to make a local decision on this basis and to follow the trail with the highest concentration. The evaporation process is often modeled as a moving average over a predefined set of objects running through the system (Armbruster et al., 2006). This paper proposes a similar approach for assigning vehicles to parking rows. Vehicles belonging to a category k calculate for every row i a pheromone value P_i^k and chose the row with the best P_i^k value. Equation (2) describes this pheromone value. The total number of vehicle categories is defined as K. In this context criteria for vehicle categories are OEM, model types and the shipment destination (see also Table 1).

$$P_i^k = \gamma_1 \left| \frac{RANG(W_i^k)}{F} - \frac{RANG(G_k)}{K} \right| + \gamma_2 \frac{d_i}{D^k} + \gamma_3 \left(1 - \frac{v_i^k}{V^k}\right) + \gamma_4 \frac{\min(W_i^k)}{\max(W^k)} \qquad (2)$$

The pheromone value P_i^k consists of four terms. Each term focuses on a different target value and can be weighted by a factor γ. Except from term 3 all remaining terms use the moving average concept to emulate the pheromone evaporation. All terms and the evaporation process will be described in the following. For each category k a moving average of the last α vehicles is used to determine two key parameters. The first parameters are the most frequented sources and sinks of the specific vehicle category. These parameters are the basis for deriving distance related measures like W_i^k. The W_i^k is defined as the distance between the most frequently used source, the storage area of the parking row i and the most frequently used sink. The second parameter is the moving average of the inventory time (days at the terminal) G_k of the vehicles belonging to category k.

The first term of the pheromone value equation (2) focuses on balancing the estimated distance W_i^k and the average inventory time G_k of a category k. The basic intention of this term is to rate rows with longer estimated distance better for categories with higher inventory time and vice versa. Therefore, this term calculates the ranking position of the estimated distance factor W_i^k divided by the amount of parking Areas F and relates it with the ranking of inventory day of remaining categories.

Most of terminal inbound and outbound processes operate in a FIFO mode. Thus, vehicles with same inventory times should stand closely together. The second term addresses the FIFO principle, by relating the inventory time of the latest vehicle in a storage area with the inventory time of the oldest vehicle of category k.

The third term addresses the split of vehicles on the terminal. An obvious constraint coming from the basic yard planning is to minimize the geographical dispersion of vehicles belonging to the same category. The number of different separated storage areas per category should be as less as possible. Therefore, this term relates the volume of vehicles of category v_i^k in the parking area of row i to the overall volume of vehicles V^k belonging to category k.

The fourth term focuses on the estimated distance for a vehicle stored on the parking area of row i. It tries to avoid an assignment, which lead to long driving distances. This term is defined as the ratio between the estimated distance W_i^k based on the moving average and the maximal possible distance for category k regarding all sources, storage areas and sinks.
The pheromone value for each row can be derived with equation (1). By contrast to natural process, vehicles choose the row with the lowest value of P_i^k as the highest concentration of pheromones.

5 Simulation Results

5.1 Impact of External Dynamics

An discrete event simulation model has been set up according to section 4. This model will be used to investigate the impact of external dynamics on the conventional yard assignment and the autonomous control method for the constant and the bulked departure variant. The parameter μ^k (amplitude of the arrival function) will be varied as a source of external dynamics (e.g., stronger seasonal effects by varying order volumes of customers). Higher values of μ^k lead to stronger variations and a more dynamic situation. In this experiment μ^k is the same for every category k in one simulation run.

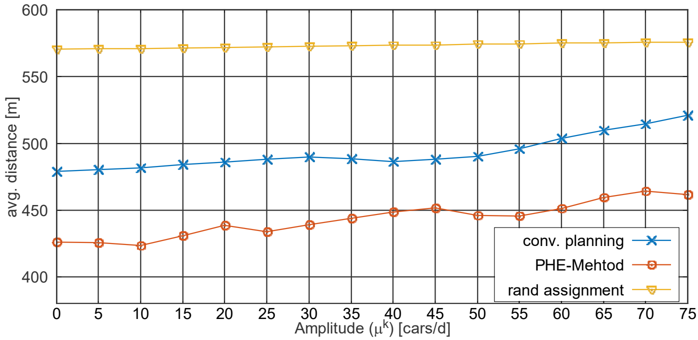

Figure 7: Simulation results for varying amplitudes

Figure 7 shows the average driving distance of all cars in a simulation run for the conventional planning, the pheromone based autonomous control method and the random assignment. The values of γ_{1-4} have been set to ($\gamma_{1-3} = 0.1$ and $\gamma_4 = 0.4$). The role of this parameters will be discussed later in section 5.2. As expected, the random assignment performs worst. Due to the random assignment possible short routes between source, storage area and sink are neglected. This leads to long driving distances. Figure 7 shows that this method is not affected by an increasing amplitude. By contrast, Figure 7 depicts a strong dependency between the conventional planning and the amplitude of the arrival function. A higher amplitude causes stronger peak periods with higher amount of arriving cars. In this situation cars are assigned to the pattern shown in Figure 6. The higher the incoming volume in a peak period, the more often secondary assignments (peak reserve) are used and occupy parking areas of other models (primary assignment) with potentially shorter routes. This leads to longer routes un-

der dynamic arrival conditions. Compared to the conventional planned situation the autonomous control method behaves different. Although, the average driving distance increases with higher values of μ^k, this effect is slightly lower compared to the conventional planning. The autonomous control method is able to cope with the external dynamics more robustly. Regarding the absolute values, the autonomous control method outperforms the conventional planning for every μ^k. This effect is stronger for higher values of μ^k. Despite higher external dynamics the autonomous control method is able to find suitable row assignments with shorter routes.
As described in section 3, the implementation of bulked departures can be seen as a source of additional dynamics. Figure 8 depicts simulation results for the scenario with bulked departures. For Figure 8, the mean vessels' capacity has been increased in steps of 100 cars per vessel (starting from 500 car up to 2000 cars per vessel). Every simulation run had a fixed mean arrival λ^k (see Table 1) and an amplitude of μ^k =50 cars per day in order to provide comparability with Figure 7. As already discussed, bigger ship capacities lead to longer inventory times. These longer inventory times affect the overall performance negatively. This can be confirmed by Figure 8. It shows that bigger vessels' capacity increase difference between conventional planning and the new autonomous control method. Like in the first scenario, the autonomous control method outperforms the conventional assignment. For vessels' capacity of 500 vehicles, the average driving distance is about 3.8% higher for the conventional planning. By contrast, this gap is for vessels' capacity of 2000 cars 11.35% higher compared to the autonomously controlled situation. In total, Figure 7 and Figure 8 confirm the hypothesis that autonomous control improve the terminals' performance under increasing external dynamics conditions induced by volatile demand

fluctuations (Figure 7) and varying bulked departures (Figure 8). Comparing both types of dynamics, the impact of varying amplitudes seems to be stronger than the vessels' capacity. Both sources of dynamics lead to differences in the internal systems' behavior for the autonomous control method and the conventional planning.

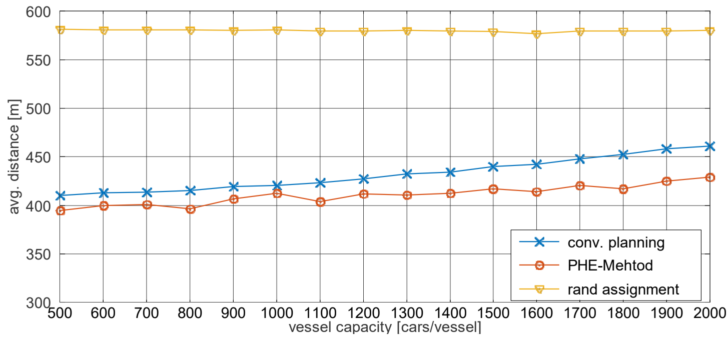

Figure 8: Simulation results for vessel capacities

Figure 9 confirms the impact of increasing dynamics on the conventional yard assignment and on the autonomous control method.

It presents scatter plots for the pheromone based method and for the conventional planning. Each plot depicts the driving distance against the terminals inventory for different points in time in a simulation run. The terminals inventory is an indicator for the externally induced dynamics. In both cases (autonomous control and conventional planning) the systems inventory level is defined by the arrival and the departure function (see also Figure 4 and Figure 5). There is no influence of the control methods on the inventory over time. Thus, this measure can be seen as an indicator of external dynamics. In addition, Figure 9 presents the average driving distance related to the terminals inventory at the same time. The driving distance depends directly on the control methods behavior. It can be seen as an indicator of the response of the control method to the corresponding external dynamics. Both upper graphs of Figure 9 show the scatter plots for the pheromone based method and the conventional planning in the scenario with a constant departure rate. Both graphs have been recorded for simulation runs with an arrival amplitude of $\mu^k = 50$. Figure 9 shows that the conventional planning leads to lower and smaller rage of average driving distances. By contrast the driving distance recorded with the pheromone based method seems to follow the inventory level. It is able to realize smaller average driving distances for situations with a low and a high inventory level and forms a nearly circular pattern. This pattern can be explained by the predefined departure delay in the scenario with constant departures. Cars arriving in situations with lower inventory levels have a better chance to be assigned to a parking row with a shorter overall driving distance. Due to the departure delay these car leave the system later in time. At this time the inventory level may be higher as it was at the time of the assignment to a row.

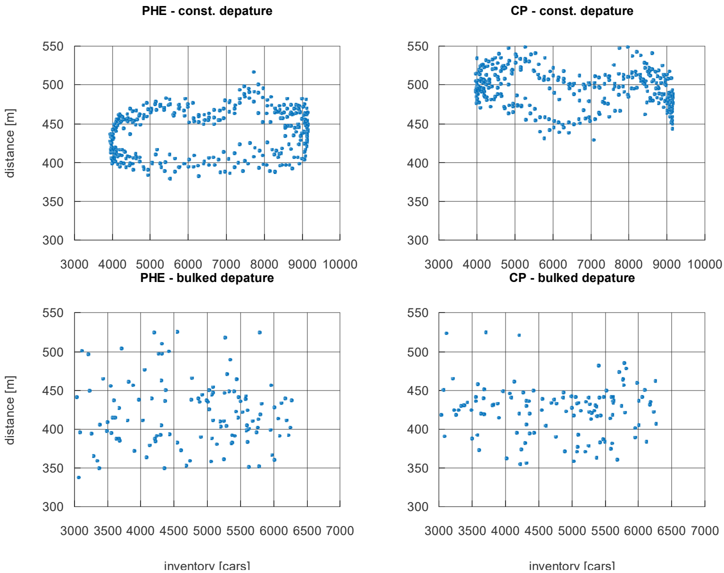

Figure 9: Scatter plots - driving distance against terminal inventory levels

Thus, Figure 9 shows a shorter driving distance of higher inventory levels and vice versa. A similar effect can be recognized for the conventionally planned situation. The graphs at the bottom of Figure 9 show the results for the scenario with bulked vessel departures (with vessel capacity of 1000 cars per vessel). Both scatter plots show a different systems behavior compared to the situation with the constant departure rate. Again the conventional planning leads to a smaller range of distances for all recorded inventory levels. However, no periodic effects can be recognized. Due to the bulked departure of cars the average inventory level is lower compared to the situation with constant departures.

Arriving ships reduce the inventory level in an abrupt manner. Cars arriving after the departure of a ship can directly be assigned to parking rows with shorter overall driving distances. Thus, the dependency of the driving distance is lower in the scenario with bulked departures. The same effect can be recognized for the pheromone based method. Driving distances and inventory levels are dispersed in the corresponding plot in Figure 9. However, the mean driving distance is still lower compared to the conventional planned situation (see also Figure 8).

5.2 Variations of Pheromone Weighting Factors

For the simulation runs presented in section 5.1. all weighting factors (γ_{1-4}) of equation (2) have been set to values, which performed well in some pretest simulation runs. In this section the impact of these weighting factors will be addressed.

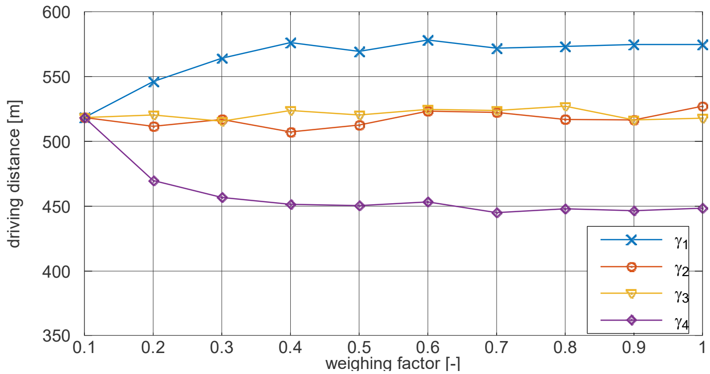

Figure 10: impact of weighting factors γ_{1-4}

Therefore, Figure 10 presents results for variations of these weighting factors regarding its impact on the average driving distance. All other values of the weighting factor have been set to 0.1 while increasing a particular weighting factor.
The first weighing factor addresses the balancing between estimated inventory times and estimated driving distances of vehicles categories. An increase of this factor leads to potentially longer driving distances. In this case equation (2) prefers a stronger balancing. It does not emphasis a greedy generation of short routes. This effect can be observed in Figure 10. As expected, the factors γ_{2-3} have a low impact on the average driving distance. Both factors aim at reducing the dispersion of vehicles of the same category on a terminal.
The fourth factor γ_4 aims at reducing the driving distance for every category of cars. Accordingly, Figure 10 shows clearly the impact of this factor on the average driving distance. In total Figure 10 shows that each term of equation (2) has its desired impact on the total driving distance.

6 Summary and Outlook

This paper presented shortcomings of conventional yard planning approaches and assumed that autonomously controlled processes could improve the performance of automobile terminals. It presented a combined bounded rational autonomous control approach with a pheromone based strategy. Furthermore, it introduces a generic modeling approach for automobile terminals for analysis of different scenarios. In the case at hand, a sinusoidal arrival function has been used to model a volatile arrival rates of

vehicles. In this scenario the new autonomous control method outperformed a simple conventional yard assignment. The analysis showed that the new autonomous control method performs best in highly dynamic situations. Moreover, this paper showed that the underlying parameters of the autonomous control method can be used to adjust the methods performance according to logistics targets of the terminal.
These results motivate for further and deeper research. First of all, a systematic investigation of structural parameters like, terminals size, distances, location of sources and sinks seems to be promising for getting a comprehensive understanding of the performance of autonomously controlled terminal processes. Although this paper showed that autonomous control is able to outperform a simple rule based yard assignment, further research will focus on more sophisticated planning methods (i.e. algorithmic approaches) and on more realistic parameters like complex OEM's model destinations mixtures and the diversified ship schedules with multiple destinations. A third research direction will be the implementation of autonomous decisions of other logistics objects like ships or trucks as well as the implementation of further autonomous control strategies.

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Efficiency Analysis of Mexican Lazaro Cardenas Port

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Purpose: The port administration is an important regulator of international trade operations, as well as a facilitator and accelerator of trade. Hence, it's important to detect the factors that must be improved to achieve greater efficiency. Therefore, the aim of this research is to determine the level of efficiency of the port system of Lazaro Cárdenas in the period 2010-2017.

Methodology: This paper develops a simulation model based on operations research, which consists in finding the optimal gantry crane assignment to improve the efficiency of the terminal, through the design of algorithms to the port subsystems services operation and analyses the effect of infrastructure and process improvements on gate congestion.

Findings: The results show that the period under analysis was inefficient. These point out the necessity of better operational strategies for the Lazaro Cárdenas port. The results also indicate that the introduction of an appointment system can reduce the average turnaround times.

Originality: This paper provide new knowledge that can be used as a new approaches to solve efficiency problems at Lazaro Cardenas port, and also the algorithm created for this analysis could be used in several ports to measure their efficiency as well.

Keywords: Logistics, Port, Efficiency, Operational Research

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1 Introduction

In order to achieve the kind of competitive international trade that can later on be translated into regional economic development, it is necessary to have the capacity to move products efficiently. For that, ports are fundamental as a tool to increase the competitiveness of external commerce.
In that sense, dry bulk cargo increased by 4.0 per cent, up from 1.7 in 2016, while global containerized trade increased by 6.4 per cent. Which shows the increase in containers' maritime terminals (UNCTAD 2018, p.1). Hence, it is an advantage for seaports the capacity to adapt to current trends and to enlarge their functions inland (Jeevan et al 2015, p. 129). Figure 1 shows worldwide TEUs traffic during the period of 2010 up to 2016. As it can be observed, there is an increase in the number of containers; this implies that there is a new challenge at the containers' terminal in order to manage a larger number of TEUs in a short amount of time and at a competitive price.

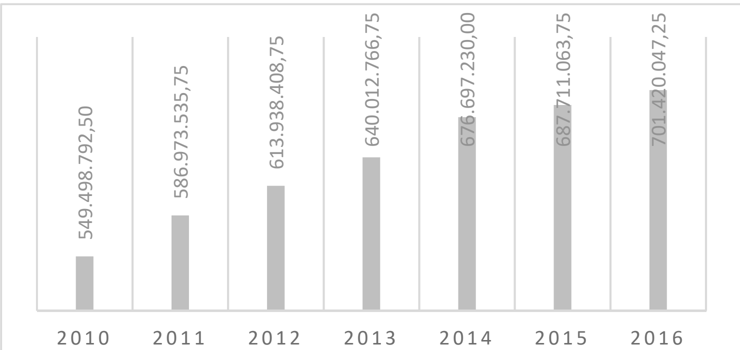

Figure 1: TEUs traffic for the period of 2010 to 2016

The international routes, the presence of hinterland companies and the international agreements are the main factors that push the ports into an international projection. However, the ports have to show the sufficient capacity to manage the international demands and to be evolving according to the interface with the multimodal transport facilitating while also encouraging international trade. That is how ports are a key element in the international trade competitiveness.

Geography of the Mexican ports has been changing since the 90's. The Mexican government's change of vision brought with it a modernization of the ports' logistic system, with development and investment on several maritime terminals improving the cargo and operational capacity while trying to decrease the infrastructure gap.

In 2017, ports in Latin America and the Caribbean rose around 6.1% on the throughput of containerized cargo. The Dominican Republic (24.0%), Colombia (13.3%), Mexico (12.2%), Panama (10.1%) and Brazil (5.0%) were the countries whose container port terminals contributed the most to the change in cargo volume versus the previous year (ECLAC 2018, P.1). With these changes the operative capacity of the Mexican ports increased from 260 million tons in 2012 to 500 million tons in 2017 (Presidencia de la Republica, 2017).

The port of Lazaro Cardenas was choose because it is the most important port in Mexico, and has worldwide infrastructure, a strategic location, connectivity and a large capacity of cargo movement.

Nevertheless, there are several factors to consider in order to improve the logistics at maritime ports, this is due to the operations a container has to face, among which we can find time pressure, minimization of resources, and all the potential problems that need to be faced in order to achieve efficiency. That is why the aim of this research is to determinate the level of efficiency of the port system of Lazaro Cardenas in the period 2010 to 2017.

2 Literature Review

The analysis of literature of similar cases were apply in order to find out the port logistic efficiency can be used to identify indicators and Muñuzuri, Escudero, Gutierrez and Guadix (2009), presented a study where they calculated two intermodal centers' efficiencies in order to identify the differences and necessities between the transport systems, such as railway, freight and maritime transport. The main variables considered for that research were: traffic, time, entries and exits.

Radonjić, Pjevčević, Hrle and Čolić (2011), with the goal of evaluating the intermodal container system developed an efficiency analysis of the containers of Serbian ports' lines of operation, used a number or variables such as: time, cost and store capacity. In order to evaluate connectivity of central ports and transport networks, Onyemechi (2010) used the length of the dock and the number of crane as variables.

Ducruet et al. (2014) measured the port efficiency of 1050 ports at 164 countries, using the data of vessels daily movements and the average answer time. They found out the efficiency's geographic pattern by country and continent.

In Robenek et al. (2012), a decision support system was proposed for the management of a terminal, it was based on a linear programming system and simulation to validate the results. Among the problems to be solved were the yard assignment problem (YAP), emphasizing the differences in operations between bulk ports and containers terminals which emphasizes the need to devise specific solutions for bulk ports.

In Cuberos (2015), a problem of crane programming and allocation of resources for different types of transport was solved, it used an adaptation for the problem of simulated annealing heuristics in order to reduce the time that the merchandise must spend in the intermodal terminals, analyzing the loading and unloading operations between the different means of transportation. The variables that were used in his study were: trains, ships, cranes that load and unload containers in the trains, cranes that load and unload containers on the ships, the instant of unloading containers, the instant of loading containers, the instant of train arrival, the instant of departure of train, the instant of ship arrival and the instant of ship departure. The conclusions were that, as the number of cranes capable of unloading and loading containers from ships and trains increases, the solutions reached by the algorithm are better. However, this improvement is not linear, which leads us to think that continuously increasing the number of cranes will not always offer better solutions.

Another work where the parameterization of the algorithm was implemented in order to solve problems of optimization presented on land transport routes of intermodal transportation is Cuberos' (2014) research. The project tries to find the parameters corresponding to the algorithm that provide better results when applied to the problem of land transport.

In Bish (2003), a problem of programming several cranes with restrictions is resolved, dividing it into three subproblems: determining the location of the container once it has been downloaded, defining the allocation of vehicles to the containers that must be transported in the terminal, and scheduling the loading and unloading operations of the cranes. A heuristic algorithm based on the formulation of the problem is developed as a transshipment problem.

Tavakkoli, Moghaddam, Makuj, Salahi and Bazzazi (2009), propose a new mixed-integer programming model for the problem of programming and assigning dock cranes in a container terminal. This work, therefore, proposes an efficient genetic algorithm to solve a programming problem of extended dock cranes (QCP) specified for a container terminal. The results obtained showed a reasonable difference of approximately 1.9% and 3.5% between the optimal solutions found. In addition, the proposed genetic algorithm reaches the almost optimal solution in a reasonable time.

In the study by Correcher, Alvarez, Tamarit and Lescaylle (2015), a mixed linear mathematical programming model is proposed for the problem of assigning berths and cranes to the ships that request the use of the dock in a container terminal. In this study, a continuous dock was considered, dynamic vessel arrival, crane assignment invariable in time and ship processing time depending on the number of cranes assigned to each one. The variables were: the vessel's berthing time, the ship's berth position, the ship's departure delay, the vessel's deviation and the ship's processing. According to the results, the model allowed the research to its optimum point of 40 vessels in a short amount of time.

Another work that proposes an optimization model integrated to a simulation model for the management of springs of continuous localization is that of Arango, Cortes, Onieva and Escudero (2012), where a genetic algorithm is developed to solve the mixed optimization model and a simulation model is proposed with three different scenarios to validate the decisions made by the model, thus the objective of the models is to minimize the operating time of each vessel. The port of Algeciras, which is the busiest container traffic port in Spain, is taken as a case study. In this work, two different traffic growth scenarios are modeled in order to validate the studied model, which was proven to be valid and, at the same time, robust in the face of future growth of the terminal's traffic and, therefore of the input data. The obtained results suppose a reduction of 8.73% in the average time of operations before an increase in traffic of approximately 21%. The use of the genetic algorithm to optimize the assignment of quay, cranes and blocks to ships has been an effective tool, since the algorithm finds a good solution in less than 3 seconds.

In Laureano, Mar and Gracia (2015), the use of the work flow diagram shown helped to determine the factors involved in port efficiency related to container loading and unloading operations. Similarly, the use given to the statistical data can be used as an example of how to apply it in the present study. This work makes an evaluation of the productivity and efficiency of the port terminal of Altamira, of the cranes used in the operations of loading and unloading of containers in ships during the third quarter of 2014. The methodology that was used is based on a statistical analysis of the operation records of the terminal, with the purpose of, when measuring the movements of the cranes, it is possible to know the productivity of the port terminal and, consequently the quality of its services. In general, it is concluded that the productivity of vessel loading and unloading operations significantly influences the production rates of the organization.

3 Methodology

The roots of operations research (OR) extend to 1800s; it was when Taylor emphasized the application of scientific analysis to methods of production. Later on in 1917, A.K: Earlang, published his work on a problem of congestion of telephone traffic; also during the 1930s Levinson applied scientific analysis to the problem of merchandising. Nevertheless, it was the First Industrial Revolution, which contributed manly on the development of, OR (Lyeme, 2012).

The council of the United Kingdom Operational Research Society (1962, p.282) defines Operational Research as “the attack of modern science on complex problems, arising in the direction and management of large systems of men, machines, materials and money in industry, business, government and defense. It goes on to state the distinctive approach as to develop a scientific model of the system; incorporating measurement of factors such as chance and risk, in order to predict and compare the outcomes of alternative decisions, strategies and controls. The purpose is to help management to determine its policy and action scientifically”.

The main goal of operations research is optimization, i.e., "the act of achieving the best possible result under the given circumstances." (Astolfi, 2006, p.2). Therefore, when operations research is applied according with the general optimization paradigm, the objective function expresses the key decision variables -selected by the researcher- that will influence the quality of decisions by maximizing (profit, product quality, speed of service) or minimizing (cost, loss, risk, time) (Bazaraa et al. 1993, p. 638). Furthermore, besides the objective function, aspects such as physical, technical, economic, environmental, legal, societal, etc. are also considered (Bronson, 1982). So that, in the context of the given model formulation, an optimal solution is selected according to the values -systematically provided- of all decision variables (Horst and Pardalos, 1995) (Marlow, 1993) and (Chong and Zak, 2001).

The operation of services in port is done through complex systems where the definition of infrastructure performance is not easy. Each port is integrated by several interrelated subsystems that provide services to ships and to final users that send or receive cargo through maritime transport. The terminals' planning, for an efficient exploration, is done in context of the medium and long terms, and must be faced as a systematic study.

There cannot be bottlenecks in the operational terminals subsystems. Therefore, it is necessary to know the capacity of each of the terminal subsystem, as well as the performance in each one of them in order to establish which of these subsystems limits its capacity. At the same time, the terminal's capacity is conditioned by the infrastructure, facilities, equipment and human resources involved in each of the phases of the port operation that take place in the terminal (Camarero et al. 2013).

A very important container terminal subsystem is the operation of the gantry cranes, where vessels are loaded and unloaded. The assignment of cranes can be considered a bottleneck if you do not have an optimal planning in place.

Container terminal operations can be grouped into four main classes, which are associated with specific processes and stages in the containe flow. It is mainly focused on the transshipment flow of containers, the associated decision problems that generally originate between the dock and the shipyard, and are:

- Assignment and programming of berth or berth allocation problem (BAP), these decisions are associated with the arrival of the vessel.
- Assignment and programming of gantry cranes (QCAP).
- Transfer operations: Containers are usually transferred inside the terminal by means of internal trucks, straddle carriers and automated guided vehicles.
- Patio operations: These decisions are associated with the storage and stacking of containers. The management of yard operations involves several decision problems.

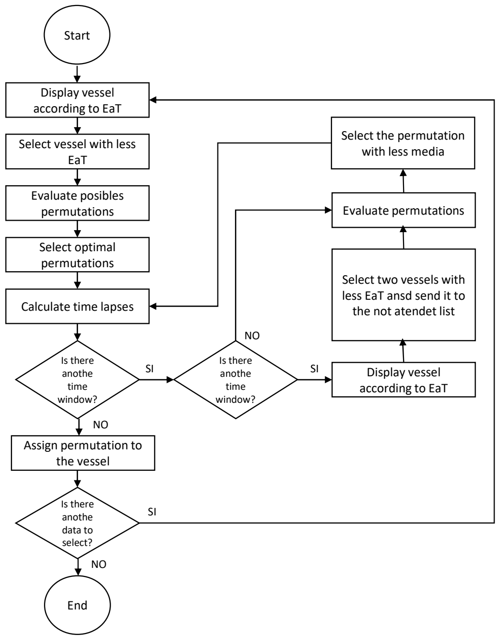

Figure 2: Algorithm of the vessel flow

The Figure 2 shows the graphic representation of the algorithm used for this research. The diagram starts with a database that consists of: set of ships (k), set of containers (C_k), the time window of each ship k which is a time lapse with an early arrival time (EaT_k) and a late arrival time (LaT_k).
The first step the algorithm uses the FIFO method (first in, first out), in which ships were ordered from lowest to highest EaT_k, this is done in order to give service to ships respecting the time window. In other words, the first ship that enters is the first ship that leaves. Once the data is sorted, we proceed to apply the basic principle of the simplex method, which is to iterate until finding the best possible solution. Therefore, the ship with the smallest EaT_k is selected for the optimality evaluation considering all the possible permutations. The variable that changes is the number of cranes assigned (Gk), this assignment will be limited to the number of cranes available in the time span $LaT_k$and LaT_k, then the permutation selected is the one that allows to reduce the operation time of ship k.
The calculation of the permutations with the selected vessels is re-done and the best permutation is chosen, in this case, it would be the permutation that obtains the lowest average operating time of the vessels. Once this calculation is made, the cranes are allocated to the ships and the assigned cranes are given the operating time corresponding to the ship so that their status appears busy (0) and cannot be assigned to another ship while they are in operation (1). This sequence is repeated until the ships of the initial list are finished. The data associated with this model is as follows:
C_k = Number of containers to be operated on the ship k
TE = Standard time by TEU.
G_k = Number of cranes operating on the ship k.
TA = Accommodation time per vessel.

n = Number of average ships per year

J = Set of cranes

K = Set of ships

Tin_k = Instant start of operation of the ship k

Tfn_k= Instant operation of the ship k

EaT_k = Early arrival time allowed for the ship k

LaT_k = Late arrival time allowed for the ship k

Tfn_j = Start of operation moment of the crane j

Tin_j = Moment of operation of the crane j

TO_k = Operation time of the ship k

TO_{jk} = Operation time of crane j assigned to ship k

BO_k = binary variable. It takes value 1 if the ship k is in operation, 0 otherwise.

EG_{kj} = binary variable. It takes value 1 if the crane is in operation on ship k, 0 otherwise.

The objective of the QCAP is to minimize the operation times of the ships that arrive at the container terminal. The algorithm to find the optimal assignment of cranes is formulated as follows:

$$MIN\ Z = \sum_{k=1}^{n}((C_k * TE)/ G_k) + TA)/n \quad (1)$$

Subject to restrictions

$$Tin_k \geq EaT_k \quad (2)$$

$$Tin_k \leq LaT_k \quad (3)$$

$$TO_k = ((Ck * TE) / G_k) + TA \quad (4)$$

$$\sum_{k=1}^{n}(BO_k) \leq 3 \quad (5)$$

$G_k \le 1$ (6)

$TO_k = TO_{jk}$ (7)

and

TO_k , TO_{jk} , Ck, TE, G_k, TA, n, $EaT_k, Tin_k, LaT_k, BO_k \geqq 0$ (8)

The objective function (1) is the average operating time. With this objective function, the aim is to minimize the total sum of the average service times in the terminal, that is, the operation time of the vessels. The ships leave the terminal when all the loading and unloading operations on them have finished.

Restrictions (2) and (3) establish when vessels must start their operation in the terminal at a time within their time window. The time window is a time lapse between an allowed early arrival time and a late arrival time and, for the purposes of this work, a time window of 30 minutes was considered. The unloading and loading operation times are considered as dependent on the working capacity of the cranes and the number of cranes assigned to the vessel. Restriction (4) defines that the operation time is considered from the moment the vessel is being docked, including the accommodation variable (TA) which includes the docking and undocking time. In the same way, standard time (TE) is important, which is the average time it takes a crane to move a TEU. Therefore, the ship's time of operation is defined by the number of containers to be operated multiplied by the standard time of the crane. The result is divided by the number of cranes assigned plus the average time it takes the ship to dock and undock in the terminal.

The containers to be operated on each vessel are known in advance, since this information is determined in the stowage plan. The loading and unloading containers are not represented separately but as sets of containers

to be operated on the ship. This simplification is due to the fact that the loading and unloading time of a container is standard for the crane.
For the model, the availability of docking will be determined by the availability of gantry cranes. In addition, the restriction (5) establishes that the terminal has three docking positions, which means that there cannot be more than three ships at the same time in the terminal.
Restriction (6) defines the number of cranes assigned, and must be greater or equal to 1. The restriction (7) ensures that the crane will remain idle until the time it is assigned to a ship. Once assigned the operating time of the crane will be equal to the operating time of the ship that was assigned to it. Finally, restriction (8) refers to non-negativity or negativity conditions.

4 Results

Understanding the performance is a concept fundamental to any business including ports efficiency where measuring of achievement against set goals and objectives is complex. After analyzing the structure of the Lazaro Cardenas port, we can point out several results.

Table 1: Average time per year, 2010-2017

Year	Real operation time	Pessimist operation time	Average operation time	Ideal operation time
2010	592.88	525.03	313.84	183.91
2011	593.29	517.96	316.74	205.04
2012	901.83	517.96	503.31	375.44
2013	802.20	486.89	387.06	281.36
2014	677.18	492.44	288.70	192.89
2015	635.23	282.89	267.03	214.33
2016	748.28	373.95	329.86	235.18
2017	619.77	277.28	267.42	208.01
MIN	592.88	277.28	267.03	183.91
MAX	901.83	525.03	503.31	375.44
MEDIA	696.33	434.30	334.25	237.02

Table 1 shows the average real operation times and the algorithm operation times for three different scenarios (ideal, pessimist and average). As

we can observe the best operation times were obtained in 2010, but that is also the year where the port had less movement of containers. This contrasts with the results of 2012, year with the worst performance and, also with the biggest number of containers received. This shows a correlation with the number of containers received and the operation time.
In order observed better these relations we calculated how many TEUs were mobilized per minute each year. The Figure 3 presents the results, and as we can see it is on 2014 when the port received more containers or TEUs per minute, and the year with less TEUs was 2010. Once we had the mobilization results, we proceeded to calculate the efficiency considering three scenarios.

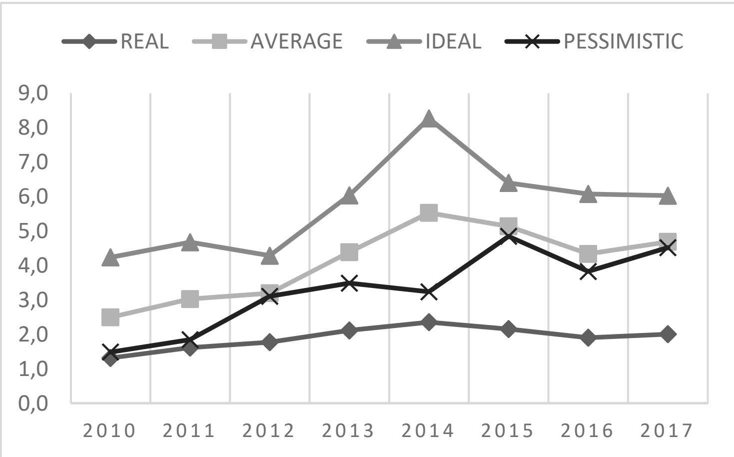

Figure 3: Average TEUs mobilized, 2010 -2017

Table 2 shows the efficiency results per year. The efficiency results can be compared in three different scenarios (ideal, pessimistic, and average). 2012 was the most efficient year if we compare the results with the ideal and average scenarios. However if we considered the pessimistic scenario, 2010 is the most efficient year.

At the same time, Table 2 shows that the worst efficiency result was obtained in 2014 with the ideal scenario, 2015 was obtained with the average scenario and for the pessimist scenario there was a tie between 2015 and 2017. The results point out the importance of an adequate planning in terms of the arrival times of the ships to the terminal. Although these represent a complex task there are different mechanisms that can be improve such as strategic planning considering tracking and tracking through different technologies.

Table 2: Efficiency index per year, 2010- 2017

Year	Ideal	Average	Pessimist	Average results
2010	0.31	0.53	0.89	0.58
2011	0.35	0.54	0.88	0.59
2012	0.42	0.56	0.57	0.52
2013	0.35	0.48	0.61	0.48
2014	0.29	0.43	0.73	0.48
2015	0.34	0.42	0.45	0.40
2016	0.31	0.44	0.50	0.42
2017	0.34	0.43	0.45	0.41
MIN	0.29	0.42	0.45	0.40
MAX	0.42	0.56	0.89	0.59

As we can observe, the operation time has been inefficient at Lazaro Cardenas terminal port for the period of analysis. However, this is a good time for start planning and for settling down the grounds of the port's organization, so the terminal can satisfy the increasing demand, and face the operational problems before the demand curve increases even more.

Based on the analysis of the obtained results, strategies can be proposed to improve the efficiency of the logistics system of the Port of Lazaro Cardenas, such as the revision of the management and organization model that is being implemented. Due to the model, it will have a direct impact on the structure of the port and its degree of flexibility, the organic vision of efficiency and the amount of work aimed at optimizing the provision of port services.
According to the considerations made, it is also necessary to review the national strategic plan in order to rebuild commercial policy guidelines, as well as the port business plan, which is updated annually. However, the importance of considering it and the importance of lowering it to an operational level is pointed out.

5 Conclusions

The present research analyzed the logistics system of Lazaro Cardenas port, in order to determine the level of efficiency of the container movement considering the operation period from 2010 to 2017. The levels of efficiency were calculated through a simulation model based on operations research, which consists in finding the optimal gantry crane assignment to improve the efficiency of the terminal, through the design of algorithms to the port subsystems services operation and analyses the effect of infrastructure and process improvements on gate congestion.

The results help to identify the factors that contribute to strengthen the efficiency levels of the port. These were obtained through the operations research methodology and, show the levels of efficiency considering the variables of execution times of loading and unloading of containers.

The port of Lazaro Cardenas is the most important port in Mexico for cargo handling and has a large presence in Latin America. It has been characterized as an industrial port due to its proximity to the most important steel zone in the country. Lazaro Cardenas port has been considered as a world-class port because it's infrastructure and movement capacity for a great variety of loads. That is why we recommend promoting the competitive advantages of the port as a logistics platform to attract more customers, as well as to take advantage of the capacity and technology offered by the port.

Regarding the aim of this research, which is to determinate the level of efficiency of the port system of Lazaro Cardenas in the period 2010 - 2017, we found out that according to the selected variables, the port wasn't efficient in its cargo movement of TEUs for that period. It is also important to point out that the efficiency levels can depend on many factors, in addition to the number of cranes assigned, the number of containers and the time window. For instance other possible factors that could influence the efficiency of the Port's logistics management are: 1) the distribution of the containers, and 2) the type of traffic to which the operated containers belong. Due to these variables mentioned above, the recommendation is for future research to include these variables too.

These points out the need for better operational strategies for the Lazaro Cárdenas port. The results also indicate that the introduction of an appointment system can reduce average turnaround times. Through the analysis of the results can be point out the necessity of improvement of the operational system, as well as the auto corrective system in order to achieve the efficiency of the port.

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III.
Sustainability and City Logistics

Digitalized and Autonomous Transport – Challenges and Chances

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Purpose: European Logistics is characterized by a matured infrastructure. Nevertheless, industry has to catch up in terms of digitalized and autonomous transport. The awareness-rising of industrial companies in this area is still limited. Therefore, the paper includes a research in order to find out the reasons for hesitations of manufacturing industry.

Methodology: For this purpose, an overview of digitalized and autonomous transport based on a literature research is given and reflected at the beginning. The focus is on new concepts to demonstrate the potentials to handle actual challenges. Subsequently, an empirical study is conducted, on which 138 manufacturing companies have participated.

Findings: The empirical study shows that governmental institutions have to work out a legal framework. Manufacturing companies are still sceptical of trends in digitalized and autonomous transport logistics. Logistics Managers still see barriers in the fields of security and infrastructure. Actually they see low chances in the next years.

Originality: Current transport logistics trend analyses usually do not challenge the topic of digitalized and autonomous transport from the users point of view. Manufacturing companies have to face a variety of challenges in the field of transport. By conducting the research, the current state and hesitations of management can be outlined.

Keywords: Digital Supply Chain, Autonomous Driving, Freight Transport, Empirical Survey

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1 Digitalized and Autonomous Transport

Due to recent development of technology and prevalent logistics framework, the relevance of digitalized and autonomous transport is growing rapidly. Technical innovations enabled an impressive development of Information and Communication Technology (I&CT) in logistics. Nowadays these innovations allow to coordinate and control all processes along the supply chain to achieve fully transparency of orders and transports.

Driven by Industry 4.0 new technology like 3D printing, Cloud Computing and Big Data have a substantial impact on how logistics manager can steer global supply chains by using software for route and cost planning or real-time tracking of goods along the supply chain. There is a significant offer of solutions which rely on these technologies.

The utilization of these technologies is essential to control complex supply chain in context of international trade. The competitiveness of the European business location is obviously determined by an efficient logistics of goods. Especially in Germany, which is at the head of European export nations (World Trade Organization, 2018), logistics industry is the third largest economic sector of the country. Due to global megatrends, which have a significant impact on supply chains (Bischof, Tschandl, Brunner, 2018, p. 120), no stop in increasing of international trade is expected. (Enzweiler, Kind and Jetzke, 2018, p. 1).

Facing the future challenges freight transport can be supported by a unique key innovation. Autonomous driving is triggering social and economic benefits for all stakeholders in the supply chain. It is obvious that in the automotive sector, especially Original Equipment Manufacturers (OEM) are investing into research and development of autonomous driving (General

Motors, 2018). This development is particularly driven by government by a huge acceleration in investments in autonomous vehicle (AV) technology and the changing of policies to encourage AVs to opening public roads. AVs also have received attention of the European Commission strategic documents in the context of broader debates on European competitiveness, climate protection, energy, employment and education within the EU 2020 strategy (European Commission, 2010).

It is incontrovertible that AVs gain in importance for transport. Freight transport can be performed in different modes of transportation (Pfohl, 2010, p. 154). Beside AVs for road transport, OEMs are also working for solution on maritime roads (Pluta, 2018). In the area of freight transport, trucks will be equipped with driving robots, which take control of the vehicle, whereby a uniform definition of AVs is still missing (Maurer, et al. 2015, p. 2).

Table 5: Stages of Automation (Lemmer, 2016, p. 12)

Stage of Automation	**Definition**
0 (Driver Only)	The driver must take control of longitudinal **and** lateral guidance permanently.
1 (Assisted)	The driver must take control of longitudinal **or** lateral guidance permanently, while robotic performs the other driving guidance. The driver has to monitor the system permanently and must be ready to take over complete vehicle guidance.
2 (Partly Automated)	The robot takes control of longitudinal **and** lateral guidance in certain situations, while the **driver has to monitor** the system. The driver must be ready to take over complete guidance.
3 (Highly Automated)	The robot takes over control of longitudinal **and** lateral guidance for determined time, while the **driver has not to monitor**. The robot is able to hand over control to the driver considering a defined preparation time for driving tasks to get ready.
4 (Fully Automated)	Longitudinal and lateral guidance are taken over by the robot for a **concrete application**. The driver does not have to monitor within the application due to autonomous guidance of the robot as long as the vehicle does not leave the concrete application.
5 (Autonomous)	The robot takes **control of full guidance** and functions whereby the **driver is not needed** anymore.

To analyze the chances and challenges it is essential to specify the research subject by identifying capabilities of AVs which are essential to join public roads. Autonomous driving describes independent driving, which is already realized as concrete applications within a determined system like the subway in Copenhagen or the "Skytrain" at the Airport of Frankfurt (Wagner, 2017, p. 9f). To concretizes the subject of autonomous driving, stages of automation are compiled to define the capability of vehicles explained in the Table above.

Starting in stage 3 the driver is able to fulfill other tasks during the ride, which is already realized. Based on expert's opinion Stage 4 will be attained in 2025, the final stage 5 in 2035 (Kossik, 2019). The final stage, which is the stage of autonomous transport is desired by industry to face the challenges of future logistics (Moring, Maiwald and Kewitz, 2018, p. 52) and offers new chances which will be presented in the upcoming chapters. This classification is based on a legislative proposal and serves as base for further law legislations (Bundesministerium für Verkehr und digitale Infrastruktur, 2015).

In 2017 law was changed to allow high or fully automated driving on German roads, as far as the system can be deactivated by humans at any time (Deutscher Bundestag, 2017). Fully autonomous driving is still not ratified in German law. In the area of freight transport legislative regulations have to be internationally valid.

Meanwhile OEMs like Daimler and Volvo have been already testing autonomous trucks on test tracks. Due to the enhancing improvement of technology, expert's opinions is that a limited amount of autonomous trucks could access public road until 2025 (Crandall and Formby, 2016, p. 29). The technological change will also affect the OEMs sustainably. This means that they will have to increase their product portfolio by including new powertrains. In future they will have to focus on autonomous long-haul trucks, going away from making a home on wheels to self-driving containers (Nowak, Viereckl, Kauschke and Starke, 2018, p. 9).

To make AV, especially autonomous trucks for freight transport road capable several perspectives have to be considered to figure out chances and challenges for logistics. Therefore, in the following chapters the chances & challenges as well as new concepts will be described to get an inside-view into the complexity, but in particular into the perception of logistics manager in the industrial sector by applying an empirical study.

2 Chances and Challenges of Digitalized and Autonomous Transport

Logistics designs the value chain along the whole production life cycle concluding goods or services, information and financial flow and connects different businesses cost-efficiently. The advantages generated in these networks by logistics is gained higher than the economic value for the customer per se (Austrian Logistics, 2018).

As mentioned before German logistics is substantial for the country's economy. In Europe the total turnover of the logistics branch amount to 1.050 Billion Euro. Just under half of the total of logistics performance is visible and perceptible by the transfer of goods. The other half takes place in form of planning, controlling and realization within the companies (Grotemeier and Wagner, 2019, p. 70).

European road transport is under increasing criticism and afflicted with many problems. Beside the high pollutant emission, the increasing volume

of traffic on roads is enhancing the level of energy consumption, noise generation and road abrasion. As a result, toll costs, fuel and fuel taxes are increasing, while the EU eastward enlargement come along with a competitive distortion due to lower incidental wage costs (Kubenz, 2008, p. 234f).
Therefore, autonomous transport is opening new opportunities and chances for logistics to meet the framework and handle challenges within the industry. The potentials of the technology are explained in the following subchapters.

2.1 Disruptions in Modern Transport Logistics

Autonomous transport is applicable in two different stages of external logistics. On the one hand manufacturing industry can use AVs for internal transport in plants, on the other hand autonomous trucks can be applied for external road utilization.
Within the factory site AVs could connect facilities like production and warehouses which are locally separated from each other. Otherwise AVs or so called Automated Guided Vehicles (AGV) can support transport processes at terminals. By applying the technology, transport routes can be shortened and empty trips avoided (Fläming, 2018, p. 372f).
Especially in the area of internal transport the potential of new technologies is already used by many companies. Electric driving systems are already applied in shuttle transport. Depending on the framework and the utilization of such applications they amortize within six years due to governmental subventions. The effect on public reputation and the decreasing of pollution is worth mentioning (Resch, 2018).

Emerging from the example above, not only automation and autonomy is disrupting European logistics. The principle of 3D-6Z is explaining three significant disruptions and thereof resulting zeroes in logistics in future, which are listed in the following Table.

Table 2: Principle of 3D-6Z (Rieck, 2018)

Disruptions	**Zeroes**
Electrification	Zero Emission
	Zero Energy
Automation/Autonomy	Zero Congestion
	Zero Accident
Connectivity	Zero Empty
	Zero Cost

The Initiative Connected Mobility (ICM) identified different benefits from autonomy in local transport. AVs can reduce noise and fine dust pollution, offers 24/7 application without taking time regulations into account, reduces transport costs by omission of drivers and employees for loading and unloading and optimization of these processes (Automotive Cluster, 2018). Due to the research subject of digitalized and autonomous transport, the following section is concentrating on the disruption of automation/autonomy and connectivity, which is the main idea of autonomous transport. Of course the disruption of electrification in transport is synonymous with those. New technologies enable to reduce emissions and energy consump-

tion and is an essential part of logistics in future. However, automation/autonomy and connectivity is also impacting the emission of pollutant as well as improving the energy consumption in transport due to optimized driving behavior.
Therefore, in the following subchapters the main focus is on the potentials concerning congestions and accidents as well as transport costs, which are seen as the zeroes with the highest impact on logistics. Emission and energy is seen within the issue of transport costs.

2.1.1 Congestion and Accidents

The "vision zero" refers to the goal of the European Commission to eliminating traffic fatalities and injuries by 2050 within the transport roadmap. In line with this goal, EU wants to halve road causalities by 2020 to become a world leader in safety of transport in all modes of transportation (European Commission, 2011, p. 10).
Nevertheless, by analyzing European strategies, the prioritization in the area of intelligent transport systems is based on the development of I&CT and does not explicitly talk about autonomy in transport so far (European Parliament, 2010).
Referring to the World Health Organization, in 2016 1.35 million road users were killed worldwide. In comparison to 2013 (1.25 million) this Figure corresponds to an increase of 8% within 3 years, which doesn't comply with the desired development of the EU strategy 2020 (World Health Organization, 2018, p. 4). Based on the National Motor Vehicle Crash Causation Survey (NMVCCS) conducted from 2005 to 2007, 94% of all crashes are caused

by drivers themselves. The most common reasons are recognition, decision, performance and non-performance errors (e.g. sleep) of humans (92%) (U.S. Department of Transportation, 2015, p. 1f).
Removing the risk of human errors would reduce accidents and vehicle-related deaths. Despite this fact it is assumed further development in technology to improve safety of AVs. This fact is supported by the first death caused by testing AVs in Tempe, Arizona in 2018(Bergen and Newcomer, 2018). However, autonomous transport could design road transport more safety and efficient due to less accidents and congestion. Affected by a lower risk for human caused accidents to reach the European Commission's goals until 2050.
Autonomous transport will have big impact on different industries. By reducing the amount of accidents and injuries especially the personal automotive insurance sector will be dramatically affected. Based on researches in the United States this sector could shrink by 40% within 25 years, while the number of accidents is estimated to drop around 80% (KPMG, 2015).

2.1.2 Transport Costs

A research by Morgan Stanley in 2013 shows the impressive cost reduction potential of autonomous vehicles. According to this, about $1.3 trillion could be saved each year by using autonomous vehicles. By comparing this cost reduction with the gross domestic product of the United States, this amount is equivalent to approximately 7% (Morgan Stanley Research, 2013). This calculation includes savings in fuel, labor costs, injuries and fatalities, increase of productivity and less congestion, which are the main areas where autonomous driving takes effect. The research firstly shows the

impact of the technology even if it has to be considered that such calculations are based on assumptions due to missing field reports.
Due to the complex sensor technology and software which is required in AVs, the sales prices of series vehicles will increase. Therefore, driving robots will be find firstly in premium segments as well as in heavy utility vehicles and touring coaches before they will be comprehensively implemented in the market. Essential prerequisite is the customer's willingness to pay higher prices in order to meet the increased production costs (Kossik, 2019).
Other studies show that the new design of trucks influences the initial price of trucks enormously. Due to the drop of driver cabins, OEMs can reduce costs by approximately €30.000 per vehicle. The additional costs for technology is estimated about €23.000 per vehicle, which means that investment costs of trucks will decrease in average by 7% (Nowak, 2018).
Another important cost factor are labor costs. Driving jobs are a major source of employment in the European Union. 4.8 million people within 28 EU countries are employed as driver in the logistics industry (European Automobile Manufacturers Association ACEA, 2018). Implementing autonomous trucks will have positive as well as negative impact on economy. In this area the cost-benefit evaluation for European economy is not possible to execute due to missing facts.

3 Concepts concerning Autonomous Transport

In the following subchapters relevant concepts of autonomous transport are described to get an overview of the possibilities of technology and their impact on European freight transport.

3.1 Physical Internet

Autonomous transport is an approach of Logistics 4.0, which includes concepts and technologies for adaptable, efficient and sustainable logistics. The thematic focus is on the vertical and horizontal integration of the value chain through merging digital and physical technologies (cyber physics). In order to fulfill the requirements resulting from customer individualization and flexibility, approaches like autonomous transport as well as self-optimization and the Internet of Things (IoT) are used. In this context elements of Logistics 4.0 are included in the concept of the Physical Internet (Lueghammer, Schwarzbauer, et al., 2015).

The Physical Internet (PI) is an intermodal and open logistics network, which is characterized by standardization, modularity and real-time capacity by utilization of the IoT (Montreuil and Louchez, 2015). In 2011 the concept was introduced as a framework to improve the efficiency and sustainability of logistics networks by sending data packets through the IoT. Logistics objects, intelligent containers and trucks, will be connected to dynamically optimize the transport flows within this network. This development in logistics realizes new business models as well as new logistics processes. (Kasztler, Wagner, Wepner, 2017).

The European Technology Plattform ALICE (Alliance for Logistics Innovation through Cooperation in Europe) has set the PI as objective of efficient and sustainable logistics by 2050 (Treiblmaier, 2016, p. 2f). By taking into consideration that the PI will have a deep impact on European logistics, a concrete demand of information is given by the manufacturing industry to work on the objectives.

3.2 Platooning

Platooning is understood as the grouping of vehicles into platoons to increase the capacity of roads, especially on highways. Prerequisite for this is an automated highway system. The platoon consists at least out of two consecutive vehicles (Lehnertz, 2018) in order to reduce air resistance of the following vehicles. Due to short safety distance fuel consumption can be decreased, which leads to energy costs saving of 4 - 7% (Elger, 2014).

I&CT allows to interchange data in real-time and synchronize breaking operations of several vehicles in order to keep the safety distance. Vehicles are able to react based on the driving behavior of the leading vehicle in the front. This leads to the saving in employees, which is another cost driver in transport. The application of platooning allows to control several vehicles by a single driver, which leads to two important approaches in platooning (Lehnertz, 2018), shown in the following Table.

Table 3: Approaches of Platooning (Own Elaboration)

Cost savings based on reduction of driver	**Cost savings based on reduction of transport time**
The application of platooning allows to reduce the amount of drivers for the transport. In future, several vehicles can be controlled by the leading driver. This concept is only applicable on highways due to the lower complexity of traffic.	The application of platooning allows to skip rest times. While one driver can control at least two vehicles on the highways, the other driver is able to rest in the driver cab. This leads to a reduction of transport times and subsequently to optimization for all stakeholders.

Based on the current availability of drivers on the labor market, platooning could be an enabler for handling the lack of drivers in future's logistics. Whereby the approach of cost saving based on reduction of transport times is the solution more likely.

One main problem of platooning is the complexity of traffic. Whilst traffic in cities is characterized by high complexity due to a high number of influence factors (different road users, pedestrians, traffic lights, etc.), on highways the complexity is less complex. This leads to problems in the transition zone highways and cities or suburban areas, where platooning is not applicable (Automotive Cluster, 2018).

Benefits of platooning can be identified in the increasing of road safety by reducing human errors and the reduction of pollution by the optimization of fuel consumption.

Countries like Netherland, Belgium and Germany are already working together to establish platooning on major roads for logistics. This concept will get more important in spite of the fact that for instance in the United States the vehicle miles travelled per year (VMT) will reach 78 billion by 2040 to meet the demand resulting from increasing desire for same-day or same-hour delivery (KPMG, 2018, p. 11)

4 Empirical Study on Transport Trends

After analyzing the situation on autonomous transport on European roads, the conducted empirical study will be presented in the following chapter. Therefore, the research design, which contains the empirical sampling and statistical analysis of the companies responding on the survey will be followed by an excerpt of the findings, related to the headed topic of this paper.

4.1 Research Design

The empirical study is based on data captured from manufacturing companies through executing a closed online survey. Objective of this survey is to research the actual state of transport logistics from the manufacturing company's point of view. The selection of study participants is done by a list-based sampling method. The focus of the empirical research is on manufacturing companies within Group C "Production of Goods" of the Austrian classification of economic activity ÖNACE (Wirtschaftskammer Österreich, 2017) with more than nine employees and a total turnover more than €2 million. The sampling is adjusted for Group C33 "Repair work & Installation" due to the fact that this group do not include manufacturing companies according to the survey's definition.

The survey was sent to 3.582 companies, whereof 194 participated in the empirical research (Response rate = 5,4%). 138 companies responded to all questions. To generate meaningful and representative findings, the survey was directed at managers within logistics-related departments with accountability for logistics tasks.

Table 4: Evaluation of dataset (Number of employees and turnover)

Number of Employees	≤ € 2 Mio.	≤ € 10 Mio.	≤ € 49 Mio.	≤ € 100 Mio.	> € 100 Mio.
≤ 9	0	1	0	0	0
≤ 49	1	25	2	0	0
≤ 249	1	5	18	3	4
≤ 550	0	1	4	16	0
> 550	0	0	1	0	26

The majority of the companies participated at the survey are classified as small and medium-sized companies (SME). However, it is necessary to take-account of the fact that due to incomplete data entries just 108 companies are considered in this statistic (Table 4).

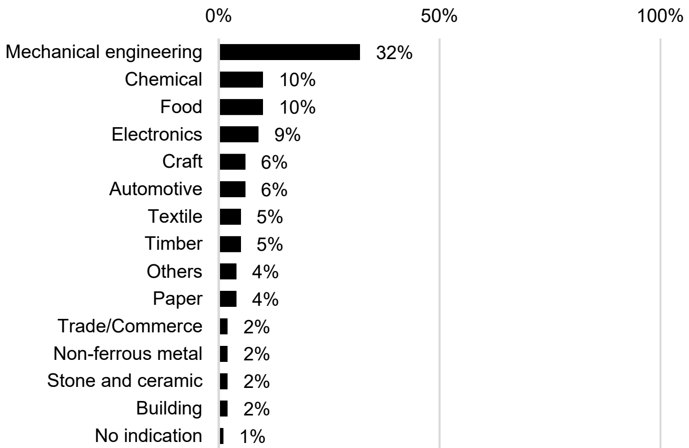

Figure 1: Industrial sectors addressed in the data set (n=138)

The Figure above shows the industry affiliation of the responding companies. The majority of the participants (32%) belong to the mechanical engineering industry. The second most frequently occurring industry is the chemical industry (10%) followed by the food industry (10%) and electronics industry (9%). "Other" includes those industries like pharmacy, synthetics, feed, consumer goods and biomass plants with 4% stake from the whole sampling.

4.2 Study on Modes of Transportation

137 out of 138 companies deliver frequently of more frequently to their customers by using European road infrastructure. The most important reason for its utilization is high flexibility and short delivery times as well as reliability of road transport. Deep sea shipping is a mode of transportation used by 27 companies frequently or more frequently due to low costs and transport risk. Especially the high mass capability is highlighted by the participants of the study. The Figure below shows that road transport is the most frequently used way of transport in manufacturing industry.

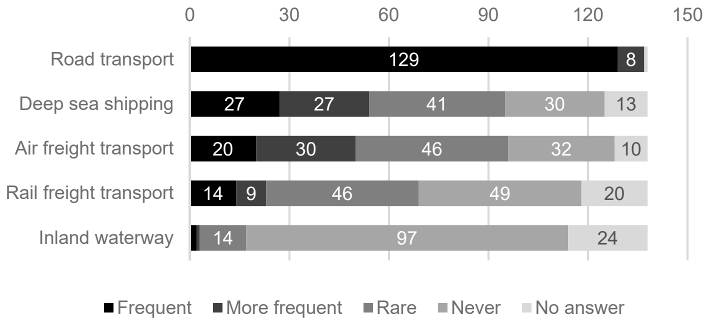

Figure 2: How frequently are modes of transportation used? (n=138)

Due to this fact, the importance of road transport for manufacturing is verified by the participants. This mode of transportation is used of companies for direct and indirect (combined or multi-level) transport.
Regarding the future development, road transport is seen as the mode of transportation with the highest increase in tonnage. Hand in hand with this development manufacturing companies see an increasing of tonnage in intermodal transport which means that road transport is going to be the key mode of transportation in future. The following Figure shows the estimation of the survey's participants in detail.

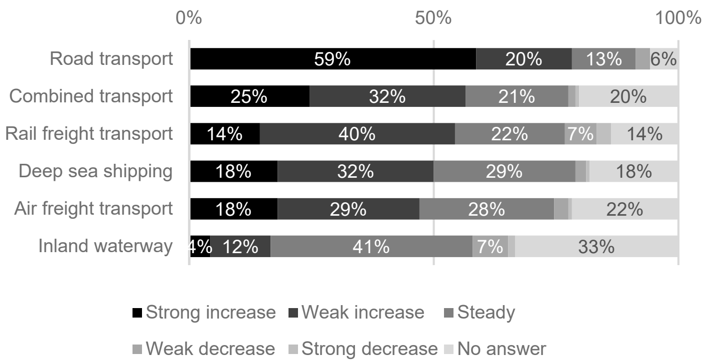

Figure 3: In the next five years, which changes in utilization of modes of transportations to you predict? (n=138)

The survey clearly points out the importance of road transport in future. The gaining in tonnage and increased utilization of the road infrastructure reinforces already existing challenges in freight transport. Therefore, the development of new concepts to face challenges and exploit opportunities like mentioned in the previous chapters will be essential to maintain and develop the existing European logistics infrastructure and the whole business sector in a sustainable way.

In general, the logistics infrastructure is seen as highly sophisticated for the actual stage of development. Due to further Austrian researches in 2019 the technical infrastructure regarding the road and grid infrastructure is well-rated by 93% of the study's participants. 70% of Austrian manufacturing companies are located less than 50 kilometers away from the next freight terminal, which confirms the logistics manager's estimation concerning the growing in importance of intermodal transport in future (FH JOANNEUM - Institut Industrial Management, 2019).

Referring on this development new concepts are more vital than ever before. The concept of Industry 4.0 is seen as the most important enabler in this area. The survey shows that manufacturing companies still hesitant regarding new solutions in logistics. Whereby 56% of the participants are interested into the concept of Industry 4.0 in the context of logistics. The concept of the Physical Internet (PI) which is explained in chapter 3.1, is not well known. 23% indicated that there is a lack of information about the long-term effect of the Physical Internet.

4.3 Study on Autonomous Vehicles

The estimation of development in the area of autonomous transport is the core of these empirical research. Therefore, manufacturing companies were surveyed regarding their opinion, if autonomous trucks will be used on public roads in the next ten years. The findings are listed in the following Table.

Table 5: Evaluation of dataset (Number of Employees and turnover)

	Fully applies	**Rather applies**	**Rather not applies**	**Not applies**	**No answer**
Autonomous transport is just a hype!	11%	31%	23%	16%	18%
Autonomous trucks show a high potential. But there are too many barriers.	31%	31%	15%	6%	18%
Trucks will drive autonomously but drivers will have to attend.	25%	47%	8%	5%	15%
In 10 years autonomous trucks will be on roads.	0%	6%	21%	53%	20%
The progress cannot be evaluated.	32%	36%	8%	4%	20%

Just 6% of the participants think that autonomous trucks will be able to join public roads in the next ten years. Nevertheless, they see a high potential in AVs. These findings can be traced back to the barriers of technology, initial costs in investment as well as legal constraints and the missing legislation in road traffic regulations. Furthermore 72% of the participants think, that drivers cannot be replaced. This means, that the respondents count on fully automated vehicles of stage 4, which will be attended by drivers.

Especially the concept of platooning could be one realistic scenario in a pre-stage of autonomous driving from the industry's point of view. Worthwhile emphasizing is that in average 18% do not answered, which shows a high uncertainty of logistics managers in this topic. To find out more about the uncertainty the participants were asked about what barriers and challenges do they see regarding autonomous driving.

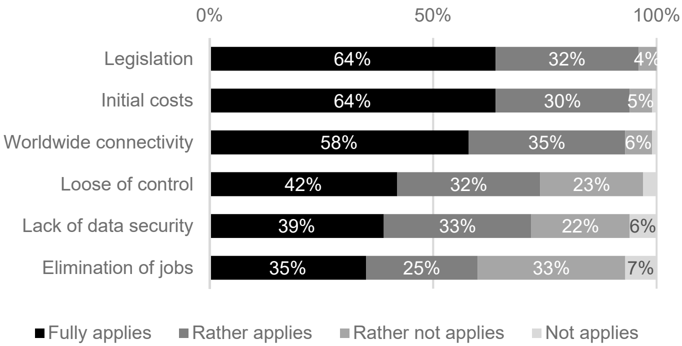

Figure 4: Which challenges/barriers are seen in utilization of autonomous trucks? (n=138)

As mentioned before, legislation is seen as the biggest barrier (see Figure 4). It appears that, that industry transferred this challenge into the area of responsibility of politics. Some countries already ratified laws for the utilization of autonomous vehicles, whereby this regulatory must be rolled put nationwide. The elimination of jobs is perceived as the lowest barrier for implementing autonomous transport. This is traced back to the lack of drivers in the logistics area. In relation to the initial costs of the investment in autonomous vehicles at the market entry, the participants rated investment costs with 64% as challenge.

By researching the advantages of autonomous trucks the rapid operational readiness is the highest rated aspect. Based on the connectivity of the fleet, participants see potentials in efficient route planning and reduction of operational costs (see Figure 5)

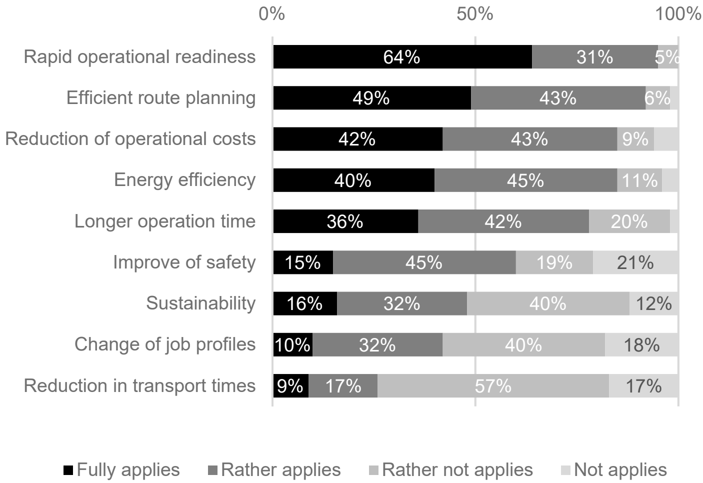

Figure 5: Which opportunities are seen in utilization of autonomous trucks? (n=138)

The results are not identical with the researches of chances. The participants are not convinced of the possibilities and chances that experts predict due to researches. Therefore, sustainability, short transport times and the change of job profiles for drivers is assessed poorly in this survey. All this could result out of the missing knowledge of manufacturing companies as well as the test results in stage 5, which just can be estimated by extrapolation on studies.

5 Concluding Remarks

The reflection of the research topics clearly shows the progressive development of I&CT. Based on this fact, autonomous driving is more than a vision of the future. Researchers expect a fast development of essential technology to enable the entry to public roads soon.
The logistics sector has to deal with many problems. Especially the lack of drivers is one of the most discussed problems. Due to the situation on the labor market, the situation will not ease up soon. On the contrary, the situation is more critical by increasing transport costs due to fuel taxes ad toll costs. Moreover, environmental and noise pollution is influencing the reputation of European freight logistics and make the situation for logistics accountable more critical.
Autonomous transport could be an enabler to handle these challenges of modern logistics. The potential of this technology is highly evaluated by experts and researchers. Nevertheless, the participants of the conducted survey do not think that autonomous trucks will be approved for public roads in the next ten years.
Furthermore, the utilization of autonomous trucks will not replace the driver's job. While experts think that autonomous trucks will not need an attendant, logistics accountants of manufacturing companies do not see the solution for the lack of drivers. They think that drivers have to join the transport as attendant, from which job profiles will change in future.
The digitalization in industry will have far-reaching consequences, also in the education of logistics employees. The education with respect to digital technology is one priority issue which has to be strengthened in future.

Finally, all these concepts do not support in handling challenges of today and tomorrow, if the public and industrial perception of these technologies will not be enhanced. The survey clearly shows, the lack of awareness and the uncertainty of logistics managers in manufacturing companies.

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Optimization and Simulation for Sustainable Supply Chain Design

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Purpose: This paper provides an overview of analytical optimization models and simulation-based approaches coping with upcoming challenges concerning the growing requirements within the field of sustainable supply chain design. It aims to combine the two highlighted solution methods in order to propose a holistic approach for decision-making support in this area.

Methodology: Initially, a literature review on current application solutions for sustainable supply chain design is given. The regarded and analyzed approaches will be clustered and allocated to supply chain design tasks. Synergetic effects of combining simulation and optimization are identified and an integrated approach is outlined.

Findings: Sustainable supply chain design tasks can be encapsulated in specific modules which are optimized simultaneously. Partial solutions are created which simplify the simulation model and reduce the necessary configurations to verify the robustness.

Originality: Current approaches focusing on sustainable supply chain design mainly use simulation or optimization. A well-defined approach using various preceded optimizations for modularized strategic tasks like partner selection, allocation of resources or determination of transport relations with subsequent verification of the results in a simulation has not been proposed yet.

Keywords: Supply Chain Design, Optimization, Simulation, Sustainability

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1 Introduction

The integration of ecological targets within the orchestration of supply chains has been focused increasingly in the most recent research work concerning supply chain management. The strategic orientation of logistics networks, the supply chain design (SCD), represents the most important challenge regarding this topic. It consists of several individual design tasks which influence each other mutually. In current research work, there is only a rudimentary consideration of these interdependencies, since individual planning approaches for the design tasks are integrated isolated from one another (Parlings, et al., 2015). The complexity of supply chain design derives from the task of simultaneously handling the individual design tasks in the best possible way and to identify and to consider the resulting interdependencies. In a best case scenario these interdependencies can be used synergistically.

Supply chain design determines the long-term operational framework and therefore can make the most influential contribution to the establishment of sustainable processes (Krieger and Sackmann, 2018). The drivers of this progressive integration of a sustainable approach include governmental regulations, economic constraints and a growing mentality to save costs caused by rising energy prices (Bonsón and Bednárová, 2015). The last aspect already implies that economic and ecological targets do not necessarily have to be mutually exclusive. On the one, hand resource savings (energy, materials, water, etc.) have a direct positive impact on economic aspects. On the other hand, a conflict of objectives can be identified. If the ecological component exerts a stronger influence on strategic design, for instance, the aim is to bundle transports optimally and to minimize express

transports. This procedure can have an extremely negative effect on the achieved service level (Bretzke, 2014).
This contribution aims to outline a solution framework that realizes a holistic strategy improvement for sustainable supply chain design (SSCD). In the course of this, the interdependencies of the design tasks must be taken into account. In terms of sustainability, it is necessary to include ecological targets within the design tasks on the basis of a uniform system of indicators. The partly negative correlation of the target values should enable the user to create trade-off solutions and compare them with his target preferences. As tools of the solution framework to be outlined, mathematical optimization methods and simulation are used. The analytical mathematical methods are particularly suitable for modeling and coping with the specific design tasks (Seidel, 2009). The simulation represents an efficient tool for the detailed evaluation of the occurring interdependencies in a supply chain. However, one major downside of simulation methods is the high modeling effort (Kuhn, et al., 2010). The linking of optimization and simulation can reduce the modeling complexity of the simulation model by generating initial solutions for individual design tasks using several optimization models beforehand. The subsequent simulation is used to evaluate the dynamic behavior of the supply chain and thus to validate the results (März and Krug, 2011). The results can be implemented into a feedback loop to improve the parameterization of the analytical methods to approximate the specific target preferences.

2 State of the Art Review

This section provides an overview of previous approaches coping with supply chain design tasks using sustainable components. In the following, the drilldown reporting procedure is described. The identified optimization-based approaches are assigned to the individual design tasks. It is quite possible that one approach addresses several design tasks at the same time. In order to realize this assignment it is initially necessary to identify these design tasks. In addition, common approaches for the integration of sustainable components into the supply chain design will be demonstrated. Finally, there is a categorization of the optimization-based solution approaches referring to the type of integration of the sustainable component and the design tasks addressed. Furthermore, simulation-based approaches and combined approaches are introduced and analyzed.

2.1 Supply Chain Design Tasks

The reference model for identifying and classifying the design tasks is the supply chain design task model introduced by Parlings, et al. (2013). It is divided into higher-level supply chain design tasks, supply chain structure tasks and supply chain process design tasks (see Figure 1).

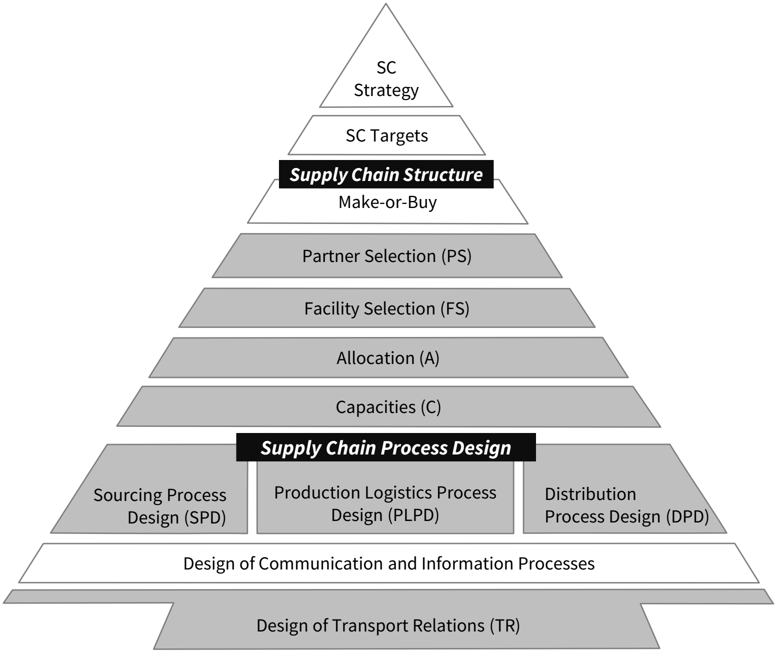

Figure 1: Supply chain design task model (Parlings, et al., 2013)

The higher-level tasks represent the definition of a strategy (Basu and Wright, 2017) and the definition of a target system (Schuh and Ünlü, 2012). Since this scope of tasks cannot be sufficiently mathematically or simulatively modeled and evaluated, approaches to solutions for these superordinate task are to be excluded in this paper. The structure of the supply chain is developed on the basis of five fundamental design tasks. The first task concerning this scope is the make-or-buy decision. First of all, it must

be determined, which of the offered services are to be provided by the company itself and which are to be purchased from other companies externally (Govil and Proth, 2001).
For services that are not provided by the customer, a partner selection (PS) has to take place. Among other choices, it must be decided whether services are to be sourced regionally or globally and whether a good is to be sourced from just one supplier or several suppliers (Rennemann, 2007).
In course of a facility selection (FS), for internal services, such as production, storage or handling of (semi-finished) products, it must be clarified how many different locations are required and where they are located. Inseparable from the choice of location is the task of allocating (A) specific products and the associated resources to the selected locations. Based on the results of the facility selection and allocation, it is necessary to implement an optimal capacity dimensioning (C). For example, production areas, stock areas or production capacities have to be dimensioned (Chopra and Meindl, 2007).
The design of the supply chain structure significantly determines the energy efficiency of the network. However, the make-or-buy decisions only indirectly influence energy efficiency in supply chains, since the definition on the use of internal or external services merely determines the division of processes among the network partners. Therefore, make-or-buy decisions are not considered in detail in this paper.
The third scope of tasks within the supply chain design is the supply chain process design. In the context of the sourcing process design (SPD), concepts for the handling and provision of incoming goods must be established. For example, the implementation of supplier concepts such as "Just-In-Time" or the introduction of a "Vendor-Managed-Inventory" can

be considered in this context. The cooperative agreement with suppliers on strategical optimal delivery rates can also be assigned to this design task. On the one hand, the production logistics process design (PLPD) consists of the decision concerning the superordinate production strategy (Wilke, 2012). A distinction, for example, can be made between the production strategies make-to-order and make-to-stock. On the other hand, the determination of the order penetration point is also one of the essential decisions within this scope of tasks (Parlings, et al., 2013). When designing the distribution processes (DPD), the most important component is to determine the number of distribution levels for each product. Following the design of sourcing, production and distribution processes, the overarching task of designing the network processes is the development of a suitable replenishment policy for each product, which defines the desired readiness to deliver (Simchi-Levi, et al., 2011).

The design of information and communication processes represents a cross-sectional task that must be addressed from sourcing through production to distribution. The design of the transport relations determines the means of transport to be used for the distribution channels.

The supply chain process design has a significant influence not only on the energy requirements of the individual processes, but also on the efficiency of the service provision. Accordingly, the introduced design task – except for the design of the information and communication processes – are central to the assessment of the energy efficiency of the network and are considered comprehensively in this paper.

2.2 Sustainable Supply Chain Design

The dynamics of supply chains are constantly changing and new paradigms in the context of ecological and social requirements must be anchored in the design of strategic processes (Paksoy, et al., 2019a). Thus, the classic supply chain design can be extended by the factor of sustainability. The aspect of sustainability is understood to mean the potential to minimize risks associated with the scarcity of natural resources, rising energy costs, environmental pollution and waste management (Srivastava, 2007). These potentials are to be integrated as additional indicators into the target system of companies within the framework of supply chain design. This leads to a paradigm shift towards sustainable supply chain design. The newly emerging target values can still be linked with the specific design tasks of classic supply chain design shown in the previous section. In the following, existing optimization models and simulation models for decision support with regard to a sustainable supply chain design will be identified and classified.

2.2.1 Optimization Models for Sustainable Supply Chain Design

In this section, optimization models for the decision support concerning sustainable supply chain design are clustered. Linear, integer linear and nonlinear optimization models are considered. The solution methods used can represent both exact and heuristic methods. The objective function and the constraints of the optimization models should be particularly focused. Since sustainable supply chain design does not necessarily have to optimize monetary values or values that can be projected to a monetary level through an intermediate step, it has to be investigated to what extent economic and ecological criteria can be included simultaneously. According to Engel, et al. (2009), a general distinction is to be made between four different modeling alternatives (see Figure 2).

The first alternative is the direct projection of ecological factors to monetary values. One possibility in terms of energy efficiency is to integrate the resulting energy costs directly into the target function. Likewise, emitted greenhouse gases can be linked to a monetary value within the scope of the emission trading scheme and can accordingly be embedded into a cost-based target function on the basis of the current price for an emission allowance. The second alternative is a weighting of individual subgoals in a higher-level objective function. For this purpose, individual scaling factors for economic and ecological sub-objectives are defined. However, when utilizing weighting factors the determination of the specific scaling factors is problematic (Rösler, 2003). A third form of integration is the establishment of ecological constraints. The consequence is that certain minimum requirements for sustainable components must always be met and that monetary values can only be optimized if the implemented constraints are maintained.

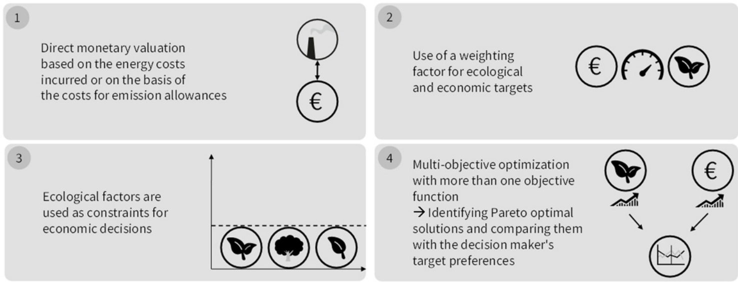

Figure 2: Modeling alternatives for optimization models concerning the simultaneous integration of economic and ecological objectives

A fourth alternative is the use of multi-objective optimization, also called Pareto optimization. As already shown, optimizations within the framework of sustainable supply chain design are characterized by contradictory target values with regard to several aspects, which influence each other negatively. A resulting challenge is to extract the most efficient trade-off solution, which tolerates losses in one or more target values (Ehrgott, 2005). The goal of multi-objective optimization is to generate a set of Pareto optimal solutions. In a Pareto efficient state, it is no longer possible to improve a target value without having to worsen another target value. The set of Pareto efficient solutions can then be used to extract a most suitable final solution based on the individual target preferences of the decision-makers (Habenicht, et al., 2003).

In the following step, existing optimization models which provide assistance regarding a sustainable supply chain design are to be clustered with regard to the four modeling alternatives introduced. Within one optimization model, several of the shown modeling alternatives can be used. For example, a multi-objective optimization with sustainable constraints may be provided or a multi-objective optimization can be used to identify suitable weighting factors, which have to be validated afterwards. The classification regarding the modeling alternative of the respective optimization model is provided in the column "OPT" of Table 1 with the numbering according to Figure 2.

In addition, the classification concerning to the extracted supply chain design tasks (see Figure 1) is provided in Table 1. An optimization model, which manages all tasks simultaneously, could not be identified. The cause for this is the high complexity of the superordinate strategic task and the numerous interdependencies of the individual decisions, which can no longer be handled simultaneously above a certain level of abstraction. Furthermore, a holistic modeling approach would cause an immense calculation effort for decision making over several periods (Günther, 2005). Nevertheless, the models often address more than one design tasks at once, whose scopes have intersections, so that a common integration makes sense up to a certain level. Accordingly, the review includes optimization models, which address at least one strategic design task and also integrate sustainable target values into the objective function in one of the modeling alternatives presented (see Table 1).

Table 1: Optimization models for sustainable supply chain design (own Figure)

Source	**PS**	**FS**	**A**	**C**	**SPD**	**PLPD**	**DPD**	**TR**	**OPT**
Abdallah, et al. (2012)	X	X	X	X			X		1,4
Arslan and Turkay (2013)					X	X			1,3
Azadnia, et al. (2015)	X				X				2,4
Chaabane (2011)	X	X	X					X	3,4
Guillén-Gosálbez and Gross-mann (2009)		X	X	X		X	X		4
Jaber, et al. (2013)					X	X			1
Lee, et al. (2018)	X		X				X	X	1

Source	PS	FS	A	C	SPD	PLPD	DPD	TR	OPT
Moham-madi, et al. (2014)		X	X				X		4
Musavi and Bozorgi-Amiri (2017)		X	X				X		4
Paksoy, et al. (2019b)	X	X	X	X				X	2,3,4
Priyan (2019)					X	X			1
Torğul and Paksoy (2019)	X				X				2,3,4
Tsao, et al. (2018)		X	X				X		3,4
Yu and Su (2017)	X								2

In the course of the state of the art review, three different branches with different scopes of application have been identified. The first branch to be mentioned is an analytically sound initial partner selection with integrated sourcing process design under the inclusion of sustainable criteria. The methods are mostly based on fuzzy logic linked to a subsequent linear optimization. There is a variety of configuration options available. Torğul and Paksoy (2019) propose a combination of a fuzzy-based analytical hierarchy process (FAHP) and fuzzy TOPSIS with a subsequent multi-objective linear optimization. Yu and Su (2017) use fuzzy logic linked with a data envelopment analysis (Fuzzy-DEA) and Azadnia, et al. (2015) implement the fuzzy logic in the context of a linear optimization with simultaneous order quantity calculation for the orchestration of partner selection and strategic sourcing process design.
As a second branch, the determination of the network processes based on the lot size determination is to be mentioned. This task includes the design of sourcing, production and distribution processes. As an approach, Arslan and Turkay (2013) propose the extension of the classical economic order quanitity (EOQ) calculation to a sustainable economic order quanitity (SEOQ). Various possibilities for the inclusion of sustainable components using linear optimization models with ecological constraints are proposed in this context. Priyan (2019) developed an extended nonlinear optimization model as a solution alternative and Jaber, et al. (2013), using another model, calculate optimal production rates in a supplier-producer relationship.
The third and largest branch is concerned with linking the nodes and edges of a supply chain network. In mathematical modeling, the decision varia-

bles represent the transport quantities of the individual products, semi-finished products and raw materials on the edges of the network. In this context the goods are allocated to the locations in the network (see Lee, et al., 2018). The design of the transport relations can theoretically take place in the same step by providing the decision variables a further index as a degree of freedom to determine the means of transport on an edge (see Chaabane, 2011). The distance bridging of the respective edge, the loading weight and the means of transport are factors which have a strong influence on the ecological balance of the network. In addition, binary activation and deactivation variables can be integrated for locations in the network in order to address the design task of facility selection (see Guillén-Gosálbez and Grossmann, 2009). This decision can be extended by a capacity-related degree of freedom so that the decision to use a node in the network has to be made considering different available capacity dimensions (see Paksoy, et al., 2019b; Abdallah, et al., 2012). If the amount of nodes in the network consists of warehouse locations on the distribution side – such as central and regional warehouses – the distribution chain of a product is also determined by this optimization (see Tsao, et al., 2018). In addition, hub allocation problems can be listed especially for the design of strategic distribution processes, which determine optimal links between transshipment points (see Mohammadi, et al., 2014; Musavi and Bozorgi-Amiri, 2017).

2.2.2 Simulation Models for Sustainable Supply Chain Design

Besides the mathematical optimization methods introduced, simulation is a common tool for decision support in the context of sustainable supply chain design. The simulation is characterized by the execution of experiments on the basis of a previously created model of an already existing or planned system. The simulation executes a performance evaluation of the model and the results are projected onto the real system to support the decision-making process (VDI, 2014). In the context of the simulation of supply chains, the dynamic behaviour of the individual locations and their links is simulated in computer models, taking into account the associated processes. The dynamics, i.e. the temporal behavior of the system, is represented by stochastic components with state changes at discrete points in time. The simulation progress takes place by the occurrence of events. For instance, in the simulation of supply chains, these events represent the arrival of a product in a warehouse or the completion of the loading of a means of transport (Rose and März, 2011).

Accordingly, simulation is particularly suitable for the holistic consideration of the interdependencies of the design tasks concerning sustainable supply chain design. Similar to the optimization models, the simulation models must also focus particularly on the performance evaluation under consideration of sustainable criteria. The evaluation is carried out by means of a key performance indicator system to be defined in advance, which determines the indicators to be evaluated after completion of the experiments. In the following, simulation studies already performed in the context of sustainable supply chain design, will be introduced.

One of the first simulative approaches was developed by Hirsch, et al. (1996), in which economically conventional goals such as service level and delivery time are simulatively investigated with regard to their ecological compatibility in order to support the establishment of environmentally friendly value networks.

Reeker, et al. (2011) identified suitable methods for the logistics expenses and performance analysis as well as for the ecological assessement, which were combined to an integrative evaluation approach based on selected key indicators. The interdepencies of the individual target values within the evaluation approach are shown transparently through a simulation.

Cirullies (2016) expanded the logistics target system to include selected ecological indicators such as resource consumption, emission values and energy consumption. Based on this, a global supply chain was modelled in a simulation software and several experiments with varying order penetration points were analyzed. For evaluation and integration into the extended key performance indicator system, transport parameters and location parameters (distance, load weight, etc., depending on the transport process) were converted into an explicitly comparable sustainability value.

2.2.3 Linking Simulation and Optimization for Sustainable Supply Chain Design

It has been shown that optimization methods are particularly suitable for supporting individual design tasks. However, a holistic evaluation is problematic. The simulation can be used for the integrative evaluation of specific scenarios on the basis of a key performance indicator system and unveils the interdependencies of the target values. On the contrary, the definition of suitable scenarios and the choice of parameters for the economic and ecological control parameters within the supply chain is somewhat difficult. A combination of optimization and simulation in the context of sustainable supply chain design is therefore an appropiate possibility to fully exploit the advantages of both tools. According to März and Krug (2011), a distinction is to be made between four different types of linking (see Figure 3).

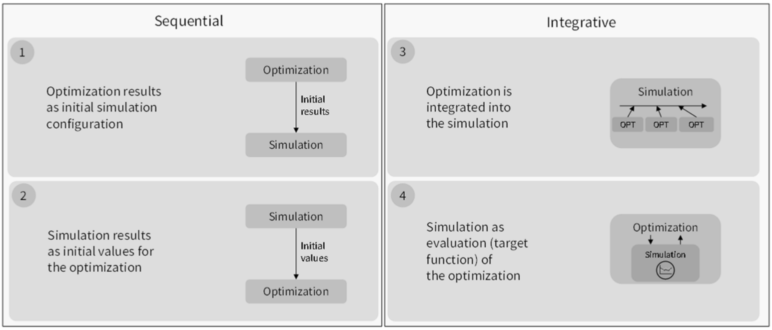

Figure 3: Types of linking simulation and optimization

A few approaches for sustainable supply chain design, which link simulation and optimization can be found. Longo (2012) developed an approach for the simulation of a network with integrated transport route optimization, which can be matched to the integrative linking type number three in Figure 3. In the system of indicators used for the evaluation, the emission values of the transports were examined among other monetary values. Guerrero, et al. (2018) propose an approach based on multi-objective optimization with subsequent simulation to ensure the statistical significance of Pareto solutions. The proposed system of indicators considers the emission values of transports carried out as well as emission values of the individual locations. The approach is to be assigned to the sequential linking type number one (see Figure 3).

The integration of sustainable components is rather sparse in the identified approaches, since only emission values of transport routes or fixed emission values of locations of the network are taken into account. Moreover, not all relevant design tasks are addressed. In the following, an innovative, holistic linking approach for sustainable supply chain design will be proposed.

3 Holistic Framework for Sustainable Supply Chain Design

The basic idea of the approach is to synchronize, adapt and extend the results from the state of the art review in an appropiate way. In the context of the identification of optimization models it could be outlined that the profound selection of several models makes it possible to address all relevant design tasks. The interdependencies can be made visible by a simulation – in particular with regard to the interaction of economic and ecological target values. The framework of the innovative approach is based on a combination and extension of the linking types number one and four (see Figure 3). This adaptation is necessary in order to benefit from the advantages of both linking types. Linking type number one is suitable for decreasing the complexity of the subsequent simulation, since initial solutions can already be used, for example, by reducing the number of potential suppliers and locations of the network in advance. Linking type number four already offers a kind of feedback mechanism between optimization and simulation. This is immensely important for the integration of sustainable target values in order to assess the dynamics and interdependencies of the interaction of economic and ecological target values within a supply chain. However, since the approach developed in this paper applies several optimization models simultaneously, the simulative evaluation should not be used for individual optimization models only, but as an evaluation for the overall aggregation of the results across all optimization models used.

In a first step, suitable optimization approaches are extracted, which together cover all relevant design tasks. In section 2.2.1, three superordinate branches have already been identified. The selected approaches from the three branches are to be projected onto the existing supply chain and are synchronized with each other so that they each optimize individual components, which can be aggregated without further intermediate steps. The objective functions to be optimized are based on a previously defined system of indicators. For each model the resulting solution is presented to the decision-makers, who carry out an initial comparison of the individual solutions with the company goals for each optimization model, which results in an initial weighting of the target values. However, the results only consider fixed static periods and usually do not reflect any periodically dynamic effects. To address this issue, a simulation of the aggregated results is executed afterwards. Since the interaction of the aggregated optimizations can deliver a changed overall solution due to mutual interdependencies and the time component, a new evaluation is performed based on the system of indicators. This overall evaluation is in turn presented to the decision-makers, who can adapt the weightings of the individual target values in the optimization models within a feedback loop taking into account the revealed causal relations. Subsequently, a new simulation with aggregated evaluation takes place. This process is repeated until the overall result matches the company goals to be achieved. An overview of the developed framework can be seen in Figure 4.

The first optimization deals primarily with the partner selection. The use of an approach based on the fuzzy set theory with subsequent linear optimization has emerged as state of the art method in literature research.

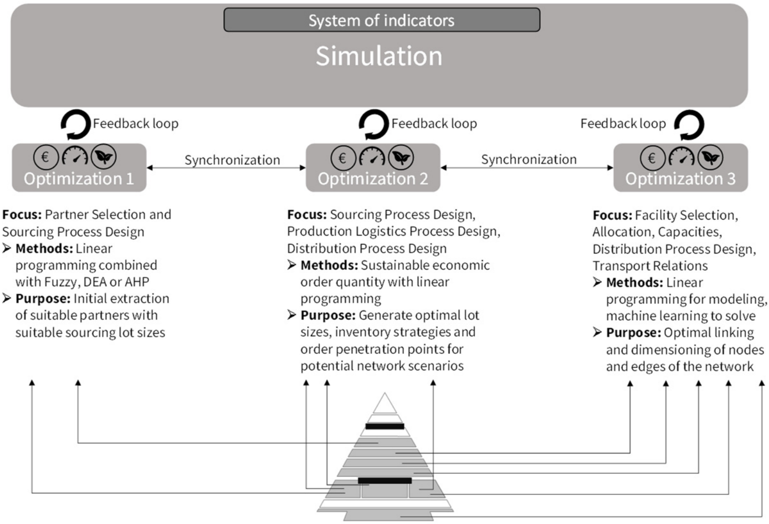

Figure 4: Holistic framework for orchestrating sustainable supply chain design (own Figure)

The criteria to be evaluated should be as consistent as possible with the overall sustainable performance indicator system. The benefit is a complexity reduction of the sourcing nodes of the network to be initially considered. If, in addition, a sourcing strategy is integrated into the model concerning the calculation of optimal sourcing lot sizes and reordering cycles, the sourcing design task is covered simultaneously.

In the second initially isolated optimization, the design of the network processes is the main topic. The determination of potentially optimal lot sizes and replenishment strategies for sourcing, production and distribution is realized, for example, by calculating a sustainable economic order quantity with coupled linear optimization. As a further result, order penetration points to be selected for the individual products can emerge.

The third optimization is responsible for connecting the nodes and edges still available for selection. Each product, semi-finished product or raw material is assigned to a sourcing location, a production location or a distribution location. The company's own locations are dimensioned accordingly with regard to the required resources. To realize the allocations, the resulting edges must be described explicitly with regard to the means of transport to be used and the transport quantities. Since this optimization usually exhibits the highest solution and modeling complexity, heuristic methods are primarily suitable as solving methods. The application of artificial intelligence and machine learning can play a decisive role in finding solutions. Methods such as neural networks or multi-agent systems are becoming increasingly popular in this context, as they are characterized by fast processing of large and complex amounts of data and outperform other solution methods in terms of solution quality and convergence speed (Hellingrath and Lechtenberg, 2019).

The three optimizations have to be adapted to the respective network and synchronized in such a way that the results can be integrated into a simulation software without further effort. Feedback loops may include adjustments to individual models. These adjustments could affect the other optimizations so that they have to be customized simultaneously. The proposed framework is not be regarded as fixed and can be extended modularly by further varying modules and objectives.

4 Conclusion

This paper pointed out that many common optimization models and simulation studies already exist in the field of sustainable supply chain design. In addition, it was highlighted that the combination of the two tools has an immense potential concerning this topic. However, previous combined approaches only address individual supply chain design tasks in isolated cases. Therefore, they cannot make any statements about the interdependencies that occur between the tasks with regard to the dynamics of a supply chain. The integration and evaluation of energy efficiency and ecological factors is also insufficiently developed and has no feedback mechanisms.

The innovative holistic approach proposed in this paper addresses all relevant supply chain design tasks and guarantees a sufficient integration of ecological parameters in all components based on a superordinate individual key performance indicator system. Selected state of the art methods are modularly linked and synchronized so that occurring interdependencies of the dynamics of a supply chain can be transparently identified and evaluated. In addition, the feedback loops, which can be performed as often as requested, provide a progressively better configuration with regard to the user's preferences.

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Sustainable City Logistics: Rebound Effects from Self-Driving Vehicles

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Purpose: This paper investigates direct and indirect rebound effects caused by the implementation of different types of car driving technologies – electric cars, high-autonomous, and fully-autonomous vehicles in the sustainable city environment.

Methodology: Lifecycle Assessment analysis extended by the social and economic dimensions has been completed for the aforementioned vehicle types in order to identify, categorize, and systemize the possible negative impacts of the investigated car driving technologies within the local (city logistics) and global (world ecosphere) environment.

Findings: Differences between local and global induced negative impacts of the new driving technologies have been identified. The paper compares the most expected/unexpected rebound effects for the three types of vehicles in the local city logistics environment and under the consideration of global impacts.

Originality: The rebound effect is mostly based on energy consumption. In this research, we have identified and analyzed indirect rebound effects from the imminent adoption of self-driving vehicles that are relevant to either city logistics development or the global environmental system.

Keywords: Rebound Effect, Sustainability, Autonomous Vehicles, Life Cycle

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1 Introduction

It is estimated that 5 billion people will live in cities by 2030 (UN, 2018). This has not only a significant impact on the mobility concept's requirements, but also on the sustainable development in cities. It is not without reason that the United Nations is focusing on Sustainable Smart Cities in Sustainable Development Goal 11, i.e. cities in which all people can live together sustainably and have access to basic services, energy, housing and transportation, among other things (UN, 2018). Urbanization, sustainability, connectivity and mobility are among today's megatrends. They pose challenges to society and companies, but also offer solutions, such as the Sustainable City Logistics concept. At the same time, these solutions will only be made possible via the above mentioned developments. An overview of challenging issues of autonomous vehicles in the context of smart cities can be found in Daschkovska, Moeller, and Bogaschewsky (2019).

In science and practice it is discussed to what extent electric cars (e-cars), alternative propulsion systems or the use of autonomous vehicles in mobility concepts have the potential to contribute to climate protection as well as to meet future demands of society. Among other things, comparative Life Cycle Assessments (LCA) were conducted for electric cars, alternative powertrains and internal combustion engines, with the ecological dimension of sustainability at its core. These studies usually put only one phase of the life cycle at the center of their analysis. It thus lacks a holistic approach that takes equal account of all dimensions of sustainability as well as all product life cycle (LC) phases of a car. Furthermore, most of the LCA literature does not consider the environment of AVs and the analysis of induced and rebound effects is too short.

Against this background, we develop the Sustainability Rebound Effect Framework which is based on the theoretical model of Life Cycle Sustainable Assessment (LCSA) and a redefinition of direct and indirect rebound effects - known from energy efficiency analysis - taking into account the three dimensions of sustainability and the life cycle perspective. This framework allows for a holistic analysis as well as comparison of the three auto types: electric, high-autonomous ("hands-off") and fully-autonomous vehicles ("steering wheel optional"). In the four LC phases - raw material extraction, manufacturing, use and end-of-life management - we identify the respective critical sustainability factors that are evaluated with regard to expected rebound effects, negative impacts and drawbacks for the aforementioned car types and categorized according to their rebound type, namely global, local, direct and indirect influence.

The paper is structured as follows. After the introduction, related work in the areas of Rebound Effects and LCA in transport and LCA for Autonomous Vehicles (AVs) is presented. This is followed by definitions of autonomous vehicles, sustainability and LCSA as well as a description of rebound effects from self-driving technology. In chapter 4 we propose our Sustainability Rebound Effect Framework which is applied to the three auto types to identify potential rebounds and drawbacks. The paper ends with a conclusion.

2 Related Work

2.1 Rebound Effect in Transport

In recent years governments in many countries tried to implement sustainable concepts in order to stimulate an effective usage of the planet's resources (UN 2018). In this regard, technological progress allows to improve and even increase the efficiency of resource and energy usage. However, there are several studies that demonstrate the backside of improving energy-efficiency by technological processes in form of so-called "rebound effects" (Brookes, 1979; Khazzoom 1980). For example, the Khazzoom-Brookes postulate states that for stable energy prices improvements in energy efficiency caused by technological progress can increase the energy consumption. But in fact, even rebound effects that could exceed 30% are very often ignored in energy efficiency and energy sufficiency policies (Sorrell et al., 2018). Based on Greening et al. (2000) rebound effects can be categorized as follows:

1. Direct effects: improvement in energy efficiency can lead to an increase in energy consumption. These effects are mainly divided into substitution effects and income effects.
2. Economy-wide effects: defined as the rebound effect on the overall economy.
3. Transformation effects: technological changes can lead to changes in consumer preferences that might influence the social system and trigger changes in the production systems.
4. Secondary effects: rebound effects observed in various production or service sectors. For example, improvement in energy efficiency reduces the costs of manufacturing and therefore decreases the price of the product, which stimulates consumption. As a result, the energy demand in the production sector will increase as well.

The last two rebound effects from the above mentioned classification are indirect rebound effects, which are usually difficult to evaluate (Wang et al., 2014). Greening's et al. definition of rebound effects in the energy industry can also be applied in the transport sector. In this example, a higher efficiency of fuel leads to more driving. This is a simple example of the direct rebound effect. Dimitropoulos et al. (2016) have analyzed 76 primary studies which use a meta-regression analysis to measure the direct rebound effect in passenger road transport. It was identified that the rebound effect in these cases can average 20 % and that the long-term direct rebound effect of more fuel-efficient cars can be 32 % (Dimitropoulos et al., 2016). Another study by Sorell and Stapleton (2018) has contributed to the limited research by estimating long-run direct rebound effects in road freight transport in UK and found that rebound effects are almost two times higher as estimated by Dimitropoulos et al. (2016). The most common problem for many of these studies in estimating rebound effects is the availability of more disaggregated data.

The main finding of Ottelin et al. (2017) is that the average rebound effect from reduced driving is less than from abandoning car ownership, and in some cases it can lead to backfiring. If rebound effects higher than 100 % occur, this is known as the "backfire effect" (Sorrell, 2009). Freire-González (2019) has computed the economy-wide water rebound effect using the example of Spain and found out that an improvement in total water consumption by 50 % leads to a backfire of 100.47 %. The same phenomena can be observed in the transport sector, where, as overall energy efficiency improves, overall energy consumption and pollution increase (Binswanger 2001).

2.2 LCA in Transport

Due to the technological process' increasing speed, increasing urbanization and overall growth in the world population, city logistics today faces numerous challenges (e.g. congestion, insufficient service and deteriorating, and inadequate infrastructure) as well as an overestimated positive impact of technology improvement versus resource-energy consumption. A promising technology in the transport sector are self-driving vehicles with electric motors. With regard to LCA investigations in the automotive industry, several LCA studies with a focus on electric vehicles or components such as lithium batteries have been published (Egede et al., 2015). Hawkins, Gausen and Strømman (2012) provide a literature overview comparing the content of 51 environmental assessments of hybrid and electric vehicles. Similarly, Nordelöf et al. (2014) review 79 LCA studies that focus on environmental impacts of hybrid, plug-in hybrid and battery electric vehicles. Font Vivanco et al. (2014a) proposed an analytical framework to model the microeconomic environmental rebound effect which is based on hybrid LCA and applied to three types of electric cars where a remarkable impact at the product level is found.

Due to the lack of LCA studies that address the use phase Egede et al. (2015) develop a LCA framework that places Electric Vehicles (EVs) into a larger system of external and internal influencing factors (vehicle, user, infrastructure, and surrounding conditions) to analyze the influence on energy consumption in the use phase. The production phase of LCA is the core of Qiao et al.'s (2017) comparative study on life cycle CO2 emissions from the production of electric and conventional vehicles (i.e. internal combustion engine vehicles) in China. Further comparative LCAs covering the whole product life cycle were performed by Del Pero, Delogu and Pierini (2018) as well as by Van Mierlo, Massagie and Rangaraju (2017). While the former carry out a case study on internal combustion engines and electric cars, the latter compare the environmental aspects of mainly compressed natural gas and battery electric vehicles, along with liquid petrol gas, biogas, plug-in hybrid electric vehicles, hybrid electric vehicles and conventional diesel as well as petrol vehicles in the context of the Brussels capital region.

Bobba et al. (2018) assess the environmental impact of electric vehicles' batteries in second-use applications with an adapted LCA with the stages manufacturing, repurposing, reusing and recycling. With a focus on social aspects Traverso et al. (2018) developed a case study to assess the social impacts of a tire throughout its entire life cycle, but excluded the end of life of a tire due to inadequate data. With the growing number of battery-powered electric vehicles the challenges in managing End of Life Vehicles increase as well, such as recycling valuable materials or disposal of the hazardous waste. In order to cope with these challenges in the End of Life Management of electric vehicles Kuşakcı et al. (2019) are addressing reverse logistics networks in their work including recovery of used components, standards-conform regaining and/or disposal of chemicals, and efficient recycling of precious materials. In a conventional vehicle around 50 different metals are used, some of which are critical. Because specific recycling processes are lacking, there is a danger that these metals will be downcycled. Therefore, Ortego et al. (2018) propose the application of a thermodynamic methodology to assess metal sustainability. The aim is to identify the most critical components and, on this basis, make specific ecodesign recommendations from a raw material perspective.

2.3 LCA Methods for Autonomous Vehicles

The authors are currently unaware of any studies that investigate autonomous vehicles using the LCSA method or that systematically consider the three dimensions of sustainability equally in their analysis of AVs. However, in a recent literature review on autonomous vehicles Faisal et al. (2019) identified 33 articles that study the impact of AVs mainly regarding the aspects perceived value of travel time changes, reduction of traffic accidents, congestion and delay, reduction of Green House Gas (GHG) emissions, public health, car ownership models or urban land use due to changes in parking demand, travel time and travel distance. In summary, Faisal et al. conclude that these are typically economic, environmental, societal, legal, political and governance impacts. With regards to LCSA this would cover the use phase.

Holstein, Dodig-Crnkovic and Pelliccione (2018) discussed ethical and social aspects as well as challenges in the context of autonomous vehicles and software engineering. In addition, Milakis et al. (2017) developed a framework to explore the potential effects of autonomous vehicles (Level 1-5) on policy and society. These aspects and considerations relate to the use phase of autonomous cars. Expected positive and negative environmental effects of shared autonomous vehicles that are discussed in the literature are presented by Pakusch, Stevens and Bossauer (2018). A nearly exclusively positive view on environmental and societal implications of autonomous driving focusing on potentials and advantages is given by Eugensson et al. (2013). Their reasoning takes into account among other things autonomous systems' direct and indirect positive environmental impacts, despite increasing traffic efficiency and in the context of reduced number of traffic accidents as well as personal and societal benefits and cost savings from avoiding crashes.

Unfortunately, many of the Life Cycle Assessment studies and LCA-based tools have ignored the importance of rebound effects. In this paper, we will discover possible rebound effects that occur in the different phases of the autonomous vehicle life cycle. First, there is still lack of research on rebound effects of self-driving vehicles; second, studies on e-cars or autonomous cars only identify the rebound effect from the perspective of energy consumption and most often for the use-phase of their life cycle. Here we present a new perspective on the rebound effects in the three dimensions of sustainability (economic, ecological and social) taking into account specific factors which each belong to one of the four stages of the life cycle of self-driving cars.

The analysis in this article has an explorative character, based on our own considerations and supported by literature.

3 Autonomous Vehicle Life Cycle

3.1 Self-Driving Vehicles

Autonomous vehicles are currently being very intensively discussed in public, researched by universities and developed in the automotive industry. In the smart mobility concept self-driving vehicles have great potential to contribute to the development of sustainable cities. There are different levels of automation that could be applied. The most promising technology for city concepts are fully autonomous or self-driving vehicles which improve the efficiency of city logistics and ensure a high quality of the travel experience (Hörold et al., 2015; Chamoso et al., 2018). From the automation concept's perspective, there are five levels of automation introduced by the Society of Automotive Engineers International (SAE). This differentiation in automation levels has become the industry standard. At the first and second automation level, the driver has the possibility to influence the operational functionality of the vehicle. At the levels 3 – 5 the vehicle's driving system can operate fully autonomous, but the level of autonomous control can vary (DoT 2016). The life cycles of new technologies as well as many components of the autonomous vehicles do not differ significantly from those of electric cars. The main phases are the traditional components of automotive LCA: phase 1 - raw material extraction, phase 2 - manufacturing, phase 3 - use and phase 4 - end-of-life.

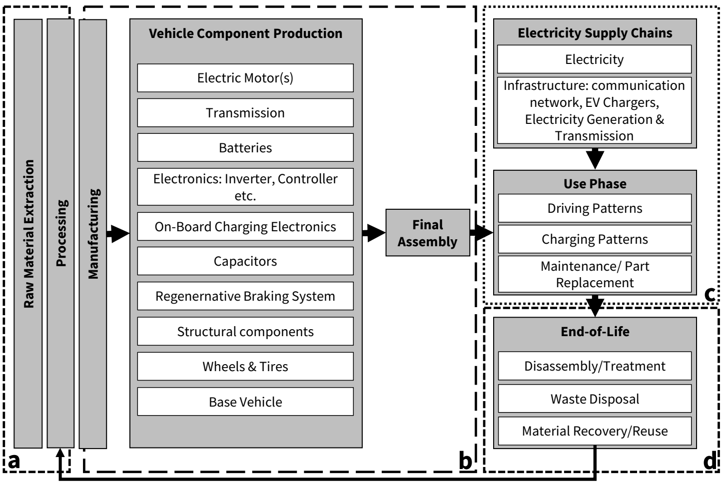

Figure 1: Simplified chart of the life cycle of an electric or autonomous vehicle (a: phase 1, b: phase 2, c: phase 3, d: phase 4) adapted from Hawkins, Gausen and Strømman, 2012, p.999.

Figure 1 shows a simplified flow chart of an LCA for electric and autonomous vehicles. The first and second phase represent raw material extraction and car production with processes in between. Additional processes include material transportation processes, production in processing facilities, distribution, electricity infrastructure, etc. (Hawkins et al., 2012). These processes are not included in the diagram. In the use phase, the availability of a communication network for autonomous vehicles is as important as the availability of charging stations. Maintenance of autonomous or electric vehicles must also be included in the use phase. In the end-of-life phase of e-cars or autonomous vehicles, the processes of battery-specific recycling or down-cycling of many components of electric-cars are very important in terms of their environmental impacts.

3.2 Sustainability and LCSA

According to the well-known definition in the Brundtland Report, sustainability is the “development that meets the needs of the present without compromising the ability of future generations to meet their own needs” (WCED, 1987). Building on this relatively vague definition, the concept has evolved into a model with three dimensions of sustainability. This approach is also referred to as the three-pillar model of sustainability or the Triple Bottom Line (TBL), which requires equal consideration of economic, environmental and social aspects of sustainability (Elkington, 1994). Alternatively, the phrase "people, planet and profit" is used to express the operational implementation in companies.

The social dimension includes aspects relating to employees, local communities and customers, such as good and safe working conditions, the opportunity to develop skills and competences, respect for human rights (e.g. prohibition of child labor and forced labor), ensuring product safety, as well as a company's activity in community work and the creation of good community relations, but also compliance with the law and the fair treatment of suppliers. The ecological dimension encompasses land use, the protection of biodiversity, effects on climate, the efficient use of energy and resources, natural resource use, waste management and recycling as well as pollution prevention, i.e. the minimization of waste and emissions, minimizing use of hazardous substances, and the use of environmentally sound materials and energy. Finally, the economic dimension covers aspects like economic growth, profit generation, job creation, innovation and technology, contribution to the local economy, infrastructure investment, cost savings, paying tax responsible and no bribery or corruption (OECD 2011; van Weele 2014).

A major challenge remains the implementation of sustainability in companies and the measurement of sustainability for products and processes. An established method, at least for the environmental dimension of sustainability, is the approach of Life Cycle Assessment, which is internationally standardized via ISO. LCA is a holistic, system analytic tool that takes into account all environmental impacts (input and output related) as well as all relevant material and energy flows for all phases of the product life cycle (Kloepffer, 2008; Finkbeiner et al., 2010). Building on this, the Life Cycle Sustainability Assessment (LCSA) concept was developed, which refers to the evaluation of the ecological, economic and social impacts of a product throughout its complete life cycle (Finkbeiner et al., 2010; Zamagni, Pesonen and Swarr, 2013). Kloepffer (2008) described the LCSA framework with the formula LCSA = LCA + LCC + SLCA, according to which the three Life Cycle Assessments Environmental Life Cycle Assessments (LCA), LCA-type Life Cycle Costing (LCC) and Social or Societal Life Cycle Assessment (SLCA) are combined. An overview of methodologies and approaches to SLCA found in the literature is provided by Jørgensen et al. (2008).

3.3 Rebound Effects from Self-Driving Technology

In the European Roadmap Smart Systems for Automated Driving (2015) rebound effects in the context of automated driving are mentioned only very briefly in the chapter on challenges, but are not further discussed. Nevertheless, rebound effects must not be neglected even though they are difficult to estimate. The comfort of AV (less stressful and tiring) will encourage people to make longer and more frequent trips, as travel time can now be used efficiently. One aspect might be, that people may prefer to live even further in the suburbs (Iglínski and Babiak, 2017), which will lead to an increased energy demand. With an upcoming era of electric or even self-driving cars the consumption of energy will be divided between other production/service industries and the rebound effects will be modified. Many new functions in autonomous vehicles require a higher quality of assistance systems, resulting in higher energy consumption. Indirect rebound effects can be observed in the transport industry. For example when due to cost savings in transportation people save time and money and consequently prefer to use a car more often, traffic in the city will increase (Gossart, 2015). Wadud et al. (2016) also found that even if automation of vehicles can reduce road transport emissions and energy consumption, the negative impacts in this context might appear mostly by fully automated vehicles. Autonomous vehicles also promise to increase the mobility of the senior population as well as for non-drivers and people with a medical condition, leading to a 14% increase in annual vehicle miles traveled only in the USA (Harper et al., 2016). An increase in 2 to 47% in travel demand for an average household in the US due to reduced energy consumption in autonomous and connected vehicles has been discussed by Taiebat, Stolper and Xu (2019).

An overall increase in energy consumption for autonomous vehicles is the main statement of recent research in the field of self-driving cars. In this paper, we propose a reinterpretation of the traditional rebound effect, which is based on energy consumption. In this research we start from the perspective that the autonomous vehicle's main user lives in the city / urban area (use phase in LCA). Anything that happens with a car in the city environment can or cannot impact not only the user himself, but also affect other phases of the auto life cycle processes. In this paper, a city in Germany represents the location of the user. From the perspective of the three-dimensional sustainability in city transport, the rebound effects are classified in this work as follows:

1. Global Sustainability Rebound Effect (GSRE): the global effect will be measured based on the world-wide spreading of rebound effects.
2. Local Sustainability Rebound Effect (LSRE): LSRE can be observed in the local city area, where the potential user has his car in daily operation. The rebound effects in this case are present only for the local city environment.
3. Direct Sustainability Rebound Effect (DSRE): DSRE can be achieved when efficiency in one of the sustainability dimensions leads to increased use of the products or related services. For example in the economic dimension of sustainability the growth of economic stability transforms into the increased use of e-cars or autonomous vehicles. As a consequence the demand for new autos increases. This demand will also increase the production of new cars while increasing the use of these sustainable vehicles in the city area.

4. Indirect Sustainability Rebound Effect (ISRE): the indirect SRE is stimulated by technological changes, which influence user preferences and behavior, which impact the aspects of sustainability and therefore increase the effects / changes on the macro-environmental level. Consider again the example of DSRE. The increased demand for autonomous vehicles led to increased production of these cars. In the case of ISRE, the chain of events will continue: More car manufacturing will require additional volumes of raw materials (increased demand for raw material), which may belong to the group of rare materials. ISRE would be (from the perspective of the car user) the indirect increase in raw material prices.

4 Rebound Effects vs. Sustainability

4.1 Sustainability Rebound Effect Framework

A theoretical framework has been developed for the systematic analysis of possible rebound effects under the three dimensions of sustainability. Table 1 shows a scheme of this framework. The framework includes different life cycle phases of the product development phase: phase 1 to phase n. For each phase, several critical aspects that may be relevant to the identification of a rebound effect are defined by the parameter $f_{i,j}^{p}$, where

p is the phase of the life cycle, $p = (\overline{1, n})$;

i is one of the sustainability dimensions, $i = (\overline{1, 3})$;

j is the index for the numbering of the critical aspect in each phase, $j = (\overline{1, m})$.

The last column of this framework demonstrates possible rebound effects that are specific for each parameter. There are four different types of rebound effects as well as their combinations that can be identified, e.g. "global, direct", etc.

Table 1: Theoretical Framework for Sustainability Rebound Effects

Item/Product	**Critical Factor**	**Rebound Type**
phase 1	$f_{1,1}^{1}$	local, global, direct, indirect
	$f_{1,2}^{1}$	
…	$f_{\mathrm{i},j}^{1}$	
phase p	$f_{1,1}^{p}$	
…	$f_{\mathrm{i},j}^{p}$	

In this study, we apply this framework to three types of electric vehicles: e-vehicle, semi-autonomous vehicle and autonomous vehicle. We examine four predefined phases of the vehicle life cycle and identify rebound effects based on the specific dimension of sustainability. For example, in the first phase "raw material extraction" for ecological sustainability, one of the critical parameters under number 2 in Table 1 is "air quality": $f_{1,2}^{1}$.

By applying the example of sustainability rebound effects in each dimension of the manufacturing life cycle phase, the following Table 2 demonstrates how the framework has been applied in this work.

Table 2: Sustainability Rebound Effects

Critical Factor	**Auto**	**Rebound Type**	**Rebound Effect**
Air Quality	all	Ecological Sustainability Rebound Effect: local, direct	Increased use of "green" and "sustainable" electric autos of all types improves air quality; people will recognize the changes in air quality and associate them with driving e-cars, therefore they will buy more of such e-cars in urban area.
Procurement Costs	all	Economic Sustainability Rebound Effect: global, local, indirect	From an economic point of view, the increased use of electric and autonomous cars in the urban area and the increased demand for such car types will lead to higher procurement prices and thus to higher production costs; at the same time the auto producers' budgets may reach

Critical Factor	Auto	Rebound Type	Rebound Effect
			their limits for other investments or innovation projects.
Working Conditions / Safety at Work	all	Social Sustainability Rebound Effect: global, local, indirect	The social rebound effect in the second phase of the e-car life cycle is indirectly reflected in a deterioration in the health and safety of workers in the factories of auto manufacturers; the effect may be due to increased demand for cars; this can also lead to greater exploitation of workers.

4.2 Ecological Sustainability: Rebound Effects

4.2.1 Raw Material Extraction Life Cycle Phase

The identified ecological rebound effects in the material extraction phase are valid for all three vehicle types and can be classified as global and indirect SREs (see Table 3). Due to by-products of extraction processes, an increase in toxins is expected, which will lead to contamination of land and water. Extraction machines with non-sustainable fuels cause a decrease of air quality and therefore negatively affect the ecosystem. Similarly, an increase in noise pollution by extraction machines might generate long-term damage for the ecosystem. Extraction machines might further increase Green House Gas emissions, which will negatively affect the climate. At the extraction site an increased demand in energy is to be expected, though the environmental impacts will depend on the energy source. Regarding the aspect of water consumption a limited availability of ground water might be caused and might result in poor quality which will destroy the ecosystem of animals and plants. The same applies to the rise in waste water. Because non-renewable resources that are limited in availability are being mined, more damaging extraction methods might be applied and as a rebound endanger the ecosystem. Due to the increasing demand for raw materials, land use could be negatively affected in the form of land sealing (e.g. factories, surface mining), and interventions in the ecosystem might lead to the destruction of habitats (flora, fauna).

Table 3: Ecological Rebound Effect in Phase 1

Critical Factor	Auto Type	Rebound Type
toxins air quality noise GHG energy consumption water consumption waste water non-renewable resources land use interventions ecosystem	all	global, indirect

It should be noted that the negative environmental impacts in phase 1 will be intensified by increased demand for raw material extraction caused by increased demand for cars in the use phase.

4.2.2 Manufacturing Life Cycle Phase

As Table 4 indicates, all identified environmental rebound effects in the manufacturing life cycle phase can be classified as local, global and indirect and apply to all auto types. Effects might be local or global depending on the location of the manufacturing site. Air quality might decrease because of production and manufacturing processes that use non-sustainable energy sources. The rebound effects here show negative effects for the ecosystem.

Table 4: Ecological Rebound Effect in Phase 2

Critical Factor	Auto Type	Rebound Type
air quality		
noise		
GHG		
water consumption	all	local, global, indirect
waste water		
toxins		
energy consumption		
waste		

In addition, the noise from factories at the extraction sites might damage the ecosystem in the long-term and GHG emissions of factories with non-sustainable fuels will negatively affect the climate. An increase in water consumption and waste water could limit the availability of ground water and deteriorate water quality, both resulting in the degradation of ecosystems. By-products of manufacturing processes can cause an increase in toxins, which might contaminate land and water as a rebound effect. Impacts of rebound effects due to an increased energy demand will depend on the used energy source. Additionally, an increase in scrap material during production processes could lead to further burdens for the ecosystem.

4.2.3 Use Life Cycle Phase

All auto types will cause local and direct environmental rebound effects in the life cycle's use phase (see Table 5).

Regarding the factor energy consumption an increase in demand is to be expected due to electricity needed for the charging of vehicles and the communication infrastructure. Potential negative impacts will depend on the source of power production. Since all three auto types will be emission free in the use phase an increase usage of cars might occur, as no negative impacts on the environment are to be expected (e.g. environment-conscious people travel more km). The use of one of the three car types will have no negative impacts on air quality and noise, and on the contrary might improve air quality and reduce noise pollution. This could also lead to an increase in car use and distances travelled. In the case of reduced noise pollution speed regulations and bans on night-time driving might be impacted and cause additional use of automobiles.

Table 5: Ecological Rebound Effect in Phase 3

Critical Factor	**Auto Type**	**Rebound Type**
energy consumption GHG noise air quality	all	local, direct

4.2.4 End-of-Life Life Cycle Phase

In the end-of-life life cycle phase all identified rebound effects can be classified as global and indirect, which is the case for all auto types. Main rebound effects are to be expected in the form of land and water contamination caused by toxins in increased waste. A second rebound effect is the destruction of the ecological system due to the increased waste at final disposals, which among other things can be attributed to more electronic waste and also due to increased land use for final disposal and recycling stations. For air quality, noise, GHG emissions, and water consumption the rebound effects depend on the chosen recycling process. An overview is given in Table 6.

Table 6: Ecological Rebound Effect in Phase 4

Critical Factor	Auto Type	Rebound Type
air quality noise GHG water consumption toxins waste / final disposal land use	all	global, indirect

4.3 Economic Sustainability: Rebound Effects

4.3.1 Raw Material Extraction Life Cycle Phase

The economic sustainability rebound effects in the first phase of the auto life cycle can be associated with critical factors such as commodity prices, less resources or new working places (see Table 7). The potential rise in commodity prices - caused by the fact that non-renewable resources are finite and depletable - can be manifested in the form of the economic indirect SRE, when the scarcity of resources leads to competition and potential conflicts on the world market of rare materials. The shortage of some resources (e.g. lithium) will be reflected in the next indirect SRE, the political tensions due to access to resources and political pressure on countries with weak political authority over domestic resources. The potential increase in employment due to higher demand in the rare material market might lead to latently poor working conditions in countries with weak labor rights.

Table 7: Economic Rebound Effect in Phase 1

Critical Factor	**Auto Type**	**Rebound Type**
commodity prices scarce resources employment	all	global, indirect

4.3.2 Manufacturing Life Cycle Phase

The topic of job creation and working conditions is also important in the manufacturing phase: the SRE can be identified as indirect effect in local and global environments in the case of growth of autonomous vehicles' production volume. An increase in procurement costs might be indirectly caused by the increased number and demand for cars in urban areas. The same increase in demand for sustainable cars will be reflected in indirect SRE for various by-products in the manufacturing (toxins, waste water, etc.) in form of additional costs for pollution or penalty payment. More autos on the markets require higher productivity from manufacturers that can resonate in another economic SRE: increase in demand on raw materials. The described factors are summarized in Table 8.

Table 8: Economic Rebound Effect in Phase 2

Critical Factor	**Auto Type**	**Rebound Type**
employment productivity	all	local, global, direct
procurement costs toxins / waste water / scrap / hazardous substances	all	local, global, direct

4.3.3 Use Life Cycle Phase

Most economic rebound effects from autonomous vehicles/e-cars appear in the use phase of their life cycle. A summary of these effects is presented in Table 9. Acquisition costs belong to the basics and at the same time, the highest ones (this aspect depends on the sharing or ownership model) that are reflected in indirect SRE, hindering the acceptance for self-driving technology. The same indirect SRE can be recognized for the initial maintenance costs of the car. The expansion of the number of charging stations directly leads to an increase in maintenance costs and to the expansion of the surface used by charging stations instead of green nature. Recharging the batteries of the new "sustainable" autos requires high voltage electricity, which currently allows for faster charging but at the same time shortens battery life. As an economic direct SRE, we can identify an increase in the cost for battery maintenance, but as an indirect SRE, charging time can lead to less flexible travelling. In the case of semi- or fully autonomous autos, the user can benefit from inductive charging with an optimal position on the charging lot.

Table 9: Economic Rebound Effect in Phase 3

Critical Factor	**Auto Type**	**Rebound Type**
acquisition cost maintenance cost	all	local, indirect
charging stations	all	local, direct
charging time battery / energy source	all	local, direct, indirect
travel cost availability energy consumption	all	local, direct
communication network / infrastructure energy demand communication network	semi, full	local, direct
data	semi, full	local, indirect
driving style travel time reliability of the system	full	local, direct

The reduced travel costs will cause a direct SRE resulting in more travelling activity. The (non-)availability of a vehicle (depends on ownership or sharing) directly affects the flexibility of users and reflects a loss of time or delays. The energy consumption factor is a classic example for a direct rebound effect. If travelling increases due to autonomous vehicles, an appropriate communication and charging infrastructure has to be guaranteed. This would mean more investments in energy supply for the automobile industry and applications (travels). An increasing number of semi- and fully autonomous vehicles in city areas will require a higher amount of supporting communication infrastructure and as a consequence a more expensive maintenance system. The energy demand for this infrastructure will lead to new investments in energy supply. In the case of semi- and fully autonomous vehicles, the topic of increased data generation is very sensitive: It is unclear to whom this data belongs (e.g. car producer, user or service provider). This indirectly generates another economic SRE concerning potential conflicts between all interested parties involved and opens up a new level of problem characterized by trust issues. Another economic direct SRE concerns the increasing volume of distance travelled due to better or even optimal driving styles of fully autonomous vehicles from the perspective of transport system optimization and thus higher road capacity. Fully autonomous vehicles are changing the lives of drivers for the better by driving faster to the destination as they offer increased road capacity, less congestions and optimal route planning. Simultaneously, time is not wasted during these long travels, but can be used productively; this efficient driving directly generates new SRE in induced travelling with more distance travelled and probably more new autonomous vehicles on the roads. On the one hand, the reliability of control systems in autonomous vehicles plays a very important role for the potential user, which, on the other hand, means a complete dependency of the user on these systems. This might involve time-consuming and cost intensive backups in the economic sense.

4.3.4 End-of-Life Life Cycle Phase

The final phase of a life cycle ends with recycling processes, which could mean a down-cycling process for all types of electric vehicles. With each cycle, the quality of the recycled material decreases, resulting in more material needed for car production. With proceeding dismantlement and treatment during the recycling process costs increase, which means that more waste produces more dismantlement work. The same challenge applies to waste management: higher costs are reflected in indirect SRE as more waste leads to more disposal.
In the situation of the global expansion of autonomous or electric vehicles, it is still necessary to build new recycling facilities that might require new land territories; indirect SRE is reflected in the fact, that areas intended for the construction of such recycling giants are not available for other land-use purposes at all or are only limited. Table 10 provides an overview of these rebound effects.

Table 10: Economic Rebound Effect in Phase 4

Critical Factor	Auto Type	Rebound Type
recycling disassembly / treatment waste disposal land use	all	global, indirect

4.4 Social Sustainability: Rebound Effects

4.4.1 Raw Material Extraction Life Cycle Phase

Social rebound effects, resulting from increased demand for cars and associated with the raw material extraction phase are all classified as global and indirect for all types of vehicles. Relevant factors are noise pollution, working conditions and safety at work, child labor, and water consumption as well as the use of conflict minerals (see Table 11).

Table 11: Social Rebound Effect in Phase 1

Critical Factor	**Auto Type**	**Rebound Type**
noise working conditions / safety at work child labor water consumption conflict minerals	all	global, indirect

While heavy noise at the extraction site negatively impacts the health of the employees as well as the health of the people in the surrounding communities, the limited availability of ground water and the associated decrease in water quality are detrimental to the living conditions of the population in terms of less drinking water and to local farmers who cannot irrigate their soils. Working conditions and safety at work could be particularly problematic in phase 1, and especially in the global context: i.e. the health and safety of workers will be endangered and exploitation of workers is possible. Next to the problem of forced labor, child labor and therefore the exploitation of children could increase and lead to them not having access to education. In addition, the procurement of minerals classified as conflict minerals may support wars and military conflicts in the respective countries and regions. Overall, this can result in the exploitation and endangerment of the local population.

4.4.2 Manufacturing Life Cycle Phase

In phase 2, expected rebound effects can occur both globally as well as locally and are to be classified as indirect (see Table 12); they emerge from all three car types alike. Noise pollution in the manufacturing and production processes is stressful for the employees and negatively affects their health, but also the living conditions for the local communities. Second, the issue of working conditions poses a risk to the health of employees and their occupational safety could be jeopardized. A further problem could therefore be the exploitation of the workforce.

Table 12: Social Rebound Effect in Phase 2

Critical Factor	**Auto Type**	**Rebound Type**
noise working conditions / safety at work	all	global, local, indirect

4.4.3 Use Life Cycle Phase

Table 13: Social Rebound Effect in Phase 3

Critical Factor	Auto Type	Rebound Type
noise safety	all	local, direct
trust / data protection	semi, full	local, direct
free time energy consumption	full	local, indirect
travel time acceptance accessibility (100 % mobility) comfort driving sytle	full	local, direct

The social SRE of noise and safety aspects is reflected in all types of electric cars in longer distances travelled as the vehicle noise is reduced directly and the safety conditions are increased. For semi- and fully autonomous vehicles, the factors of trust and data protection might lead to direct and local social SREs in the form of more kilometers driven and an increased demand for new cars. Self-driving vehicles allow users to get more free time due to the optimally planned driving process. This leads to another social SRE, as additional free time could be spent for more travels and/or not sustainable travel modes (plane, ship), or for other activities that consume even more energy. In addition, fully autonomous vehicles are associated with an increasing need for real-time communication and energy infrastructure in the urban environment, which can indirectly lead to further social SREs, such as "electro smog" in the city, which may become a potential health risk.

The social acceptance of fully autonomous vehicles is a further critical factor: In the case of complete acceptance, it might lead to a social SRE in the form of increased usage of cars; conversely, doubts might hinder technological development. A major advantage of autonomous vehicles is 100 % mobility for all levels of the population including the elderly, physically challenged, children and those without a driver's license. That might increase the total number of travels and eventually more cars will have to be produced. Extra comfort when travelling with autonomous vehicles could increase the distance traveled; people who used to travel by foot, public transport or bike might switch to autonomous vehicles, which could reproductively influence their health. Another social aspect that should not be forgotten is the difference in driving style: In autonomous vehicles, driving may be very comfortable and less stressful for many people, but many users like to drive themselves, resulting in an unexpected social SRE such as loss of control during the driving process or less determined driving preferences. An overview of the presented rebound effects is given in Table 13.

4.4.4 End-of-Life Life Cycle Phase

Table 14: Social Rebound Effect in Phase 4

Critical Factor	Auto Type	Rebound Type
working conditions disassembly		
waste / final disposal	all	global, indirect
toxins / hazardous materials		

As the volume of new types of e-cars in urban areas might increases, the situation at recycling stations may worsen as recycling processes become more intense and can lead to social SRE in the form of negative health effects for workers. An increase in auto industry waste and more housing near recycling stations will be reflected in a social SRE, such as the degradation of the living conditions of local communities. More toxins or hazardous substances in the recycling process can endanger public health. See Table 14 for a summary of the rebound effects.

5 Conclusion

In this paper, we discussed the subject of rebound effects, which can even occur in a sustainable city environment. Rebound effects in three sustainability dimensions of urban areas were analyzed throughout the life cycle of three types of e-vehicles. For the analysis, a specific framework was proposed that combines LCA parameters and sustainability dimensions. The study presents several possible and sometimes unexpected REs that are identified from the perspective of city logistics. The results show mostly negative effects of an uncontrolled implementation of autonomous vehicle technology. At the moment these rebound effects only have theoretical relevance, because in practice they are very difficult to evaluate and validate. A large number of them indicate potential risks in various areas of a sustainable city after full implementation of autonomous vehicle technology, and require a closer investigation on this topic, either for vehicle producers or for urban developers.

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IV.
Business Analytics

Business Analytics on AIS Data: Potentials, Limitations and Perspectives.

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Purpose: As maritime digitalization progresses, great opportunities for maritime transport arise: The introduction of the AIS opened up a number of possibilities and perspectives for increasing efficiency, automation and cost reduction using business analytics and machine learning in the supply chain and maritime sector.

Methodology: Various analysis and forecast techniques of machine learning as well as interactive visualizations are presented for the automated analysis of ship movement patterns, risk assessments of encounter situations of two or more ships as well as anomaly detections or performance indicators to quickly extract key figures of certain ships, routes or areas.

Findings: In addition to a comprehensive representation of relevant potentials and business analytics areas of AIS data, the feasibility and associated accuracy of the data mining and machine learning methods used are described. In addition, limitations will be shown and perspectives especially on autonomous surface ships will be discussed.

Originality: At present, there is no information platform that bundles the areas described in the previous sections in a central source. Previous work has either been limited to the visualization of historical and current ship movements or deals with narrowly limited individual questions of isolated applications.

Keywords: Business, Analytics, Maritime, Traffic

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1 Introduction

As maritime digitalization progresses, great opportunities for the shipping and port industries as well as for plant manufacturers and service providers arise: Increased efficiency can be expected from the latest processes in the developments of ship operation and port logistics. Emission and fuel reductions can be achieved by prospective voyage and route planning.

With the introduction of merchant ships being equipped with transmitters of the Automatic Identification System (AIS) in 2004, shipping was able to reach a first milestone on the way to digitalization. The automated exchange of position, speed, course and other data from ship to ship or ship to shore station has increased the efficiency and safety of maritime traffic. In addition to the monitoring of ship movement data, timetables and weather conditions are used for the overall monitoring of maritime traffic, so that over the past few years a wealth of data of unexpected dimensions and possibilities has accumulated.

Shipping companies and seaports face a multitude of challenges: These include in particular the ship size developments of recent years, in which the absolute number of ships calling at German seaports is stagnating, but the gross tonnage of ships, the absolute total handling volumes and the number of unusually large vessels are growing continuously. These facts have the consequence that more and more transshipments are concentrated in relatively small time windows for port operations. Environmental influences have a significant impact on ship travel times and terminal operations. Strong winds cause challenges within the seaports: For example, transshipment facilities have to cease operation and seagoing ships have

to adjust their speeds. In the case of shipping companies, emission and associated efficiency regulations currently play a central role - not only due to the obligation on ship-owners to report CO2 emissions from voyages to, from and within European waters since 1 January 2018 - but also within the high-profile context of climate change.
Previous applications based on AIS data focus on the visualization of historical and current ship movements or circumvent the influence of environmental data on ship movements only in a theoretical way. The investigation and inclusion of the effects of environmental influences on the travel times, routes and movement patterns of ships are not given much consideration in previous applications. In addition to a more efficient and optimized control of maritime traffic and the maritime supply chain, the focus is on ensuring safe navigation and thus avoiding collisions - especially on the open sea.
Due to the ever-increasing volume of data and the simultaneous exponential growth of computing and storage capacities, the use of machine learning methods also offers immense possibilities in the maritime logistics sector.
After a short introduction to existing techniques on ship motion modelling and analysis, this paper gives an overview of the possibilities for the analysis of AIS data. In addition, limits and further perspectives of the application of AIS data for efficiency enhancement and analysis of business figures are shown.

2 Literature Review

Most of the machine learning methods used in maritime logistics are applied on AIS data. The current state of these applications is depicted in the following sections. A distinction is made between route prediction and the modeling of ship movements, i.e. representing arrival times, in order to increase the planning horizon of maritime stakeholders and thus to act more cost-efficiently and with more foresight. In addition, many algorithms are used for anomaly detection and collision avoidance tasks.

2.1 Route Forecasts

Within the route forecasting waypoints of a ship to a given destination or port of destination are to be predicted. In principle, route forecasting algorithms can be divided into two categories (Lo Duca, et al., 2017): point based and trajectory based. In the first case, the surrounding area of a ship is divided into parcels. For the individual ships in the close range, the algorithms estimate the probabilities of cells being targeted next by the ships under consideration. The probabilities are calculated using different machine learning algorithms. In trajectory-based estimation, clusters are generated from historical data. These contain all routes and serve to structure them.

The most frequently referenced work on the application of machine learning methods on AIS data is the "framework for anomaly detection and route prediction" created by Pallotta et al. (Pallotta, et al., 2013). Based on historically generated routes, algorithms for the classification and prediction of routes and for the subsequent anomaly detection of unnatural ship maneuvers are developed. Given a sequence of state vectors - consisting of position, course and speed values of a certain ship type - each compatible route is assigned a-posteriori probabilities in relation to the ship affiliation of the corresponding route. This allows the future position of the ship to be predicted for a given ship and a pre-specified period. Clustering algorithms are also used (Hexeberg, et al., 2017) to identify historical route patterns, assign ships to these patterns and predict the trajectory based on these patterns. Lo Duca et al. (Lo Duca, et al., 2017) use a k-Nearest-Neighbor classifier for ship route prediction. The point-based probability of reaching a grid point is calculated and the most probable route is given. In accordance to the AIS framework (Pallotta, et al., 2013), there is only a relatively small prediction horizon of 60 minutes. Zhang et al. (Zhang, et al., 2018) describe a method how AIS data can be used to select suitable routes. By analyzing the movement patterns of those ships that have already completed a planned route, the shortest route can be generated algorithmically: In a first step, significant changes in direction of individual trajectories are identified and used as turning points. A clustering method (Density-Based Spatial Clustering of Applications with Noise, DBSCAN) groups common turning points of all routes. This results in the last phase of automatic routing. The shortest route between start and end is searched for from the generated graph (Zhang, et al., 2018), (Dobrkovic, et al., 2015). Vespe et al. (Vespe, et al., 2012) present an unsupervised learning approach for incremental learning of movement patterns without specifying a priori contextual descriptions. The extraction of waypoints is the first step, followed by the definition of sea routes and routes connecting them. The proposed algorithm uses AIS data to detect changes in the course over ground for the proximity of the observed position; if these values reach a certain threshold value, a new turning waypoint is added to the list (Vespe, et al., 2012).

Neural networks are often used for regression tasks, also with regard to large data and deep learning tasks being the current state of the art for speech and image recognition. Mao et al. (Mao, et al., 2018) use a neural single hidden layer feedforward network with random hidden nodes for route prediction. Perera et al. (Perera, et al., 2010), (Perera, et al., 2012), use artificial neural networks for the tasks of classifying and identifying ships as well as tracking multiple ships. By means of an extended Kalman Filter, ship states are estimated and ship trajectories are predicted (Prévost, et al., 2007). In addition to the above, neural networks are also used in (Simsir & Ertugrul, 2007), (Simsir & Ertugrul, 2009), (Xu, et al., 2012) and (Zissis, et al., 2015).

In addition to neural networks, Bayesian networks are often used to generate "normal" behavior, such as, for example, done by Mascaro et al. (Mascaro, et al., 2014), (Mascaro, et al., 2010) or Aoude et al. (Aoude, et al., 2011), particulate filters (Mazzarella, et al., 2015) are used for clustering ship trajectories and Ornstein-Uhlenbeck processes (Pallotta, et al., 2014) and genetic algorithms (Pelizzari, 2015) are used for trajectory prediction as well.

2.2 Estimation of Arrival Times

The speed and arrival time estimations are usually accompanied by the route forecasts, since the speed is included in the route calculation for most approaches. Nevertheless, some methods, in which the speed or arrival time are estimated, are presented below.

Arrival times are an important factor for the handling of arriving ships in ports. Even forecasts with an accuracy of 60-70% can significantly improve process planning at the terminals (Yu, et al., 2018). If the route between two points, for example between two AIS data intervals, is to be predicted, the most common method (Posada, et al., 2011) is the Constant Velocity Model. A linear movement from point A to point B is assumed. Further information on speed and course, possibly contained in the AIS data, will not be taken into account. The speed is set as constant. The temporal/spatial proximity plays a considerable role in the accuracy of the forecast. The greater the distance between the points, the less accurate the interpolation. This problem occurs with predictions of more than one hour, as well as in offshore areas (Mazzarella, et al., 2015). By assuming constant speed, however, environmental influences that could lead to a reduction in speed are not taken into account.

Besides neural networks, support vector machines (SVM) are often used for classification and regression tasks. Using a kernel that calculates distances between two objects, a SVM divides a set of objects into classes so that the widest possible area around the class boundaries remains free of objects (EliteDataScience, 2017). Parolas et al. (Parolas, et al., 2017) use SVMs and neural networks to estimate the time of arrivals for container ships in the port of Rotterdam. The weather and environmental conditions are clustered and used alongside the AIS data for training. Fancello et al. (Fancello, et al., 2011) use artifical neural networks to estimate ships arrival times in ports to allocate human resources in container terminals.

2.3 Collision Avoidance and Anomaly Detection

Besides the use of the AIS data for the modelling of basic ship movements, there are possibilities to AIS for collision avoidance, safety assessment as well as anomaly detection with regard to the early detection of these anomalies to enhance safety. Using a Deep Neural or Bayesian Network, the navigation and movement behaviour of ships during an encounter can be studied and predicted for real-time encounters (Perera, et al., 2010), (Perera, 2018). By adjusting the ship's speed and course, a route recommendation for a collision avoidance manoeuvre can then be given. Same approaches are developed by (Lee, et al., 2004), (Xue, et al., 2008), (Mou, et al., 2010), (Simsir, et al., 2014) or depicted by (Tu, et al., 2017).

In addition to collision avoidance, there are possibilities for anomaly detection of historical and current ship movements using machine learning methods. Examples are Gaussian Processes (Rasmussen, 2006), (Kowalska & Peel, 2012) or Bayesian Networks (Johansson & Falkman, 2007), (Mascaro, et al., 2010) or (Mascaro, et al., 2014).

2.4 Approach

For the above mentioned reasons, in the field of maritime logistics, where highly efficient process control is an important success factor, there are numerous opportunities to apply machine learning methods to the upcoming arising problems to gain efficiency increases. Nevertheless, in contrast to the above-mentioned applications, there exists almost no tool for the first descriptive analysis of movements in real-time. The BigOceanData portal (BigOceanData, 2019), which provides first descriptive analyses of historical data, is the only one to be mentioned here.

The need for an interactive solution for the automated analysis and evaluation of maritime and environmental data is in the limited range of information available from providers already operating on the market for the processing of AIS data. An exemplary study of information providers already operating on the market showed that data collected using AIS receivers is usually mapped only.

The innovative value of the presented research project can be seen in the automated consolidation, processing and provision of data relevant to shipping from various sources. To the knowledge of the project participants no comparable data processing system exists - neither nationally nor internationally. However, in isolated cases and with different methods AIS data again and again for risk and safety analyses is used.

3 Data Source

In addition to AIS data, other data sources were identified and subsequently used. These are described below.

3.1 Automatic Identification System (AIS)

The Automatic Identification System, which was introduced by the International Maritime Organization (IMO) to increase safety in shipping, provides the basis for the following analyses and methodologies. The data transmitted by AIS transmitters for the exchange of nautically relevant information between different ships and shore stations can be classified into three categories: Static data, dynamic data and Voyage-related data.
According to the recommendations published by the International Telecommunication Union (International Telecommunication Union, 2014), AIS data exchange consists of 27 different messages. The most relevant for navigation are the position reports (messages 1, 2 and 3) and the static and voyage-related ship data (message 5). For further analysis, the Fraunhofer internal AIS dataset for the period 01.02.2016 - 30.04.2018 of the North Sea and Baltic can be used to validate and check the theoretical approaches. Nevertheless, it should be noted within this paper, and in particular in the presentation, that various methods have been performed on a smaller, generalized dataset in order to ensure the real-time capability. The following parameters are used:

ShipID: In order to comply with data protection guidelines, each ship will be assigned an independent identification number (ID)
ShipType: Integer in accordance with (International Telecommunication Union, 2014)
Length: The overall length of the vessel in meters
Breadth: The breadth of the vessel in meters
Draught: The maximum current draught in meters
Latitude: latitude in 1/10 000 min (90°, north = positive (according to 2er-complement), South = negative (according to 2er-complement)
Longitude: longitude in 1/10 000 min (180°, east = positive (according to 2er-complement), West = negative (according to 2er-complement)
SOG: Speed over ground in 1/10 knots
COG: Course over ground in 1/10 = (0-3 599) °
TH: True Heading from 0 to 359°

3.2 Environmental Data

In addition to the ship movement data of the AIS, weather and environmental data is used for further analyses, such as the determination of the resistance of a ship, to estimate emissions. In particular, the parameters wind, wave and current, which are often depicted on a $m \times n$ grid, must be used for this purpose. For the correlation of the environmental and AIs data, the projected AIS data on a $1000\ m \times 1000\ m$ grid is given by
$x_i = \frac{\lambda_i \cdot 1852 \cdot 60}{100}$ and $y_j = \frac{\varphi_j \cdot 1852 \cdot 60 \cdot \cos\left(\lambda_i \cdot \frac{\pi}{180}\right)}{100}$
with λ_i and φ_j being longitude and latitude for $i = 1, \dots, n$ and $j = 1, \dots, m$.

4 Potentials: Analysis Framework

In the following, the results of the analyses and, in a first step, the data flow are presented. During the presentation of the paper the Jupyter Notebook (Project Jupyter, 2018) framework will be presented.
AIS data is checked for plausibility within a first step and outliers are removed. In addition, the existing position data of the AIS of individual ships are merged into trips from a port of departure to a port of destination. For details on the methodology extracting trips, reference is made to (Jahn & Scheidweiler, 2018). The data is then processed within a Jupyter Notebook (Project Jupyter, 2018) framework using Python.
Within the framework, investigations are made on the automated analyses of historical and current ship movements in specific sea areas. In addition, potentials for risk and safety assessments of different encounter situations of ships or areas, for the anomaly detection of historical and current ship movements are examined. Within Python, descriptive analyses, regressions as well as clustering or supervised machine learning algorithms such as neural networks or decision trees are used.

4.1 Movement Patterns

A central aspect of the analysis of movement patterns should be the automated representation of historical ship movements for the identification of distributions and movement patterns of ships as well as route patterns and traffic densities of different ship classes and sea areas. In addition to the classical motion pattern analysis, the potentials of automated frequency analyses of ships as well as distribution analyses of speeds and courses along predefined areas are to be investigated and the corresponding methods developed. Methods for calculating the time ships spend at berths and on anchorage will also be presented.

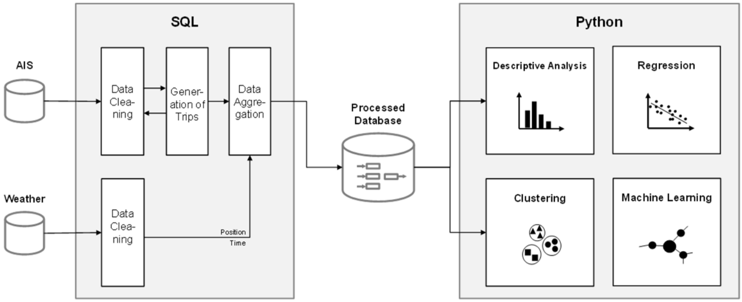

Figure 1: Visualization of the data flow of AIS and weather data. Preparation and consolidation of these within SQL and following analyses in Python.

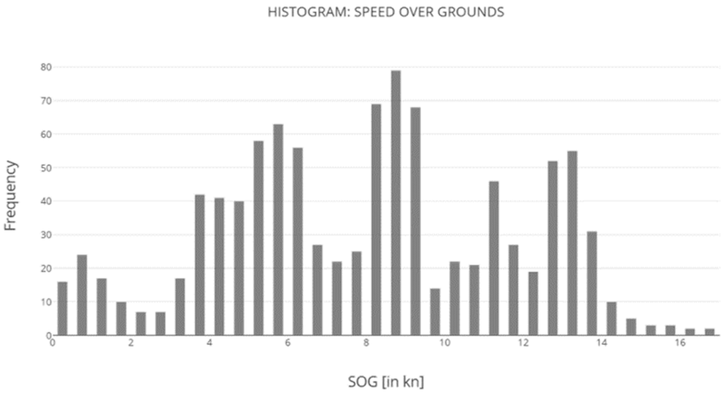

Figure 2: Histogram of the speeds over the ground of the study area

4.1.1 Motion pattern of a predefined area

For the identification of historical movement patterns within an area, this region has to be specified. Using the boundaries given by φ_{min} , φ_{max}, λ_{min} and λ_{max} ship movement data can be automatically extracted from the database. In addition to chart displays, histograms can be generated for the initial analysis of the speeds or courses, but also of the static data of the ships. Figure 2 shows an example of the speeds prevailing in the study area. In addition to histograms, other descriptive tools such as box plots can of course be used for visual analysis of the position distributions of the measurements of the parameters and edited interactively.

4.1.2 Motion Patterns of Predefined Routes

With a given departure and destination port, ship movement data of the AIS is extracted from the specified area of the database. In the following, the movements from Rotterdam to Hamburg are considered.

In addition to the data described in section 3 transmitted via the AIS, trip data is used within the following analyses. In addition to motion pattern representations, histograms and scatter plots are created for visual analysis. The diagram below depicts the travel times from Rotterdam to Hamburg. With the help of this information, possible ship times can be determined in real time and thus further planning of the hinterland or other resources can be carried out.

For port and shipping authorities, the automated speed analysis of voyages is of particular relevance in order to trace incidents, for example, as depicted in Figure 4.

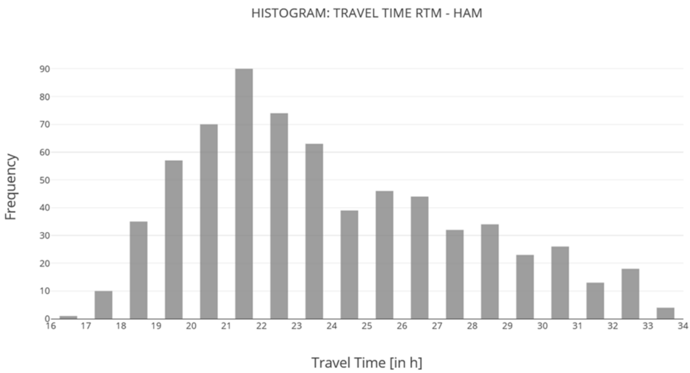

Figure 3: Histogram of the total travel times of the investigation route

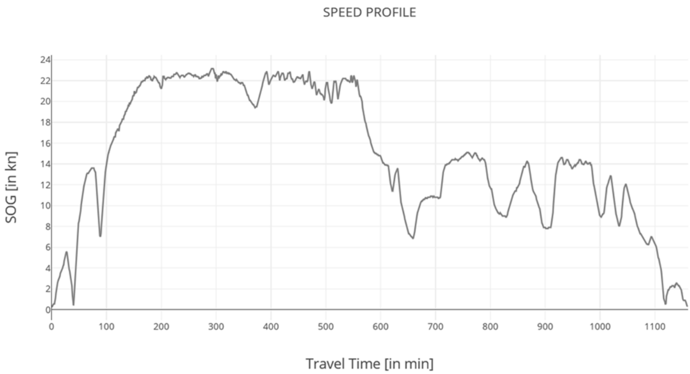

Figure 4: Average speed profile of trips from Rotterdam to Hamburg

The energy efficiency of ships is significantly influenced by the speed-dependent fuel consumption. To assess the efficiency, the travel times and speeds of ships of different sizes on specified routes are examined. For a more detailed analysis, the frequency of speeds along the route is determined for selected ship size classes. For this purpose, the velocities are derived as Froude numbers:

$$Fn = \frac{SOG}{\sqrt{g * length}}$$

where g is the gravitational force and SOG the current speed over the ground of a ship.

Froude's number relates inertia forces to gravity forces and is used in shipbuilding as an indicator of the energy loss caused by the radiation of waves in relation to the total energy loss. For regular services on a route with similar or even identical ships (e.g. ferry connections), the absolute speeds can be compared. This allows conclusions to be drawn about the efficiency of individual ships within a fleet or about the efficiency of individual operators in a direct competition situation.

4.1.3 Frequency and Distribution Analysis

In addition to the motion pattern analysis, potentials of automated frequency analyses of ships as well as distribution analyses of speeds and courses along predefined ranges are investigated and the corresponding methods developed. Figure 5 depicts the crossing positions of ships in the Kiel Canal at Sehestedt. Based on these crossing positions, lateral distributions can be determined for a later risk analysis which provides ship-owners and shipping companies with a rapid and efficient risk assessment of their own ships.

4.1.4 Berthing and Anchoring Times

Methods are developed for calculating the time ships spend at berth and at anchorage in order to draw conclusions about inefficient and thus costly waiting times for ships. The first step in determining anchoring times is to determine where vessels are at anchor assuming that the speed is larger than a specified threshold c. As an example, the average anchoring time of vessels entering the port of Hamburg in the German Bight can be determined based on the areas: 5.023 hours.

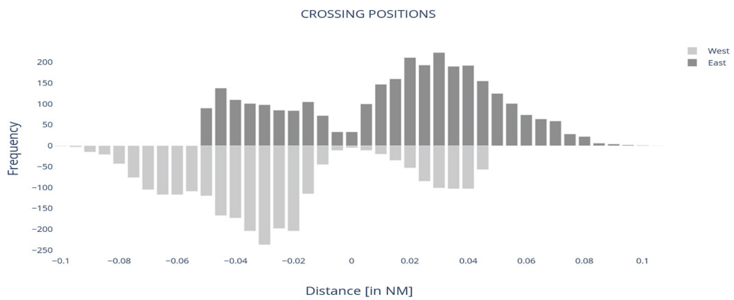

Figure 5: Histogram of the crossing positions of the study area

4.2 Risk Assessment

For the risk and safety assessment the passing distances of two ships during encounters, as well as the distances to fairway edges and barrel lines are examined. Furthermore the assessment of maximum and minimum angles of approach which a pre-defined group of ships has steered in a certain fairway are defined. The encounter situations of two pre-selected ships can be evaluated with regard to collisions and fairways with regard to their safety levels by using accident statistics. Both the current position data of the AIS

and historical movement data will be used to provide a risk profile. Encounter situations are to be assessed by determining the number of encounters in a user-defined fairway area within a defined time period. Again, the passing distance of the ships are analysed. Finally, it should be possible to assign a safety level to each fairway and a risk level to each encounter situation.
The risk indicates a numerical value which is determined by the probability of occurrence (also called frequency) and the average amount of damage. This corresponds to determining the probability of occurrenceP_i, which results in the consequence C_i from an identified hazard H_i. For the risk analysis, this is then linked with the monetary valuation U_i of the resulting consequence, so that the overall risk applies (Pedersen, 2010), (International Maritime Organization, 2007):

$$Risk = \sum_i P_i(H_i, C_i) \cdot U(C_i)$$

The following passages are components of a possible risk assessment.

4.2.1 Passing Distances

The Closest Point of Approach (CPA) between ships is the smallest distance they are likely to have without changing course or speed. Given a standard traffic situation, the CPA and the Time to Closest Point of Approach (TCPA) can be calculated based on the course over ground of the own ship x, the course over ground of the traffic ship y, the speed over ground of the own ship v, the speed over ground of the traffic ship w as well as the longitudinal distance t and lateral distance u by

$$CPA = \sqrt{\frac{(u \cdot w \cdot \sin y - t \cdot w \cdot \cos y - u \cdot v \cdot \sin x + t \cdot v \cdot \cos x)^2}{v^2 + w^2 - 2 \cdot v \cdot w \cdot (\sin x \cdot \sin y + \cos x \cdot \cos y)}}$$

For the risk and safety assessment, the distances between two ships during encounters, as well as the distances to fairway edges and barrel lines, can be recorded, analysed and visualised. The TCPA can be used to determine the urgency of an evasive action and is given by

$$TCPA = \frac{t \cdot v \cdot \sin x - t \cdot w \cdot \sin y + u \cdot v \cdot \cos x - u \cdot w \cdot \cos y}{v^2 + w^2 - 2 \cdot v \cdot w \cdot (\sin x \cdot \sin y + \cos x \cdot \cos y)}$$

For the discussion of the passing distances, those of certain areas are determined. Figure 6 presents the passing distances on the basis of percentages.

In addition, the encounter situations of two pre-selected ships can be evaluated with regard to collisions. Encounter situations shall be assessed by determining the number of encounters in a user defined fairway area within a defined time period. The passing distance of the ships is also analysed here. Finally, it should be possible to assign a safety level to each fairway and a risk level to each encounter situation.

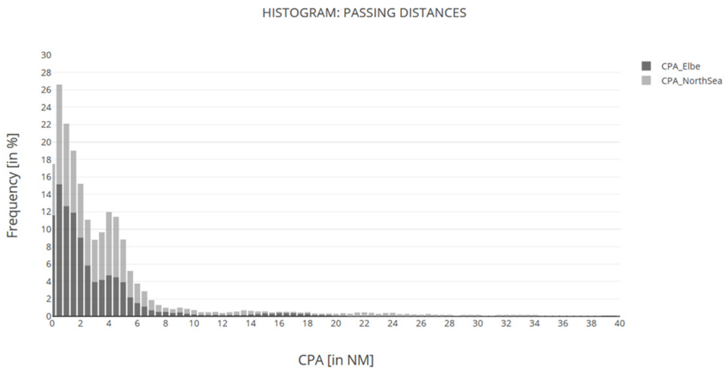

Figure 6: Representation of the CPAs in the Elbe River and the North Sea

Using the IWRAP method recommended by the International Association of Lighthouse Authorities, the frequency of collisions and groundings in a given area can be specified on the basis of information on traffic volume and composition, route geometry and bathymetry. As an example, the collision risk for the Elbe at the level of the Hamburg suburb Blankenese is 1.4%. For further information on the modelling tool, please refer to the IALA documentation (IALA, 2014).

4.2.2 Safety levels of fairways

Fairways can be assessed in terms of their safety levels by discussing domain violations from ships. Both the current position data of the AIS and historical movement data will be used to provide a risk profile.
The ship domains indicate the area around a ship which should be kept free from other ships at all times. Since a violation of this area is the prerequisite for a possible collision, encounters between two ships that do not violate the other domain can be classified as comparatively low-risk. Moments in which at least one of the domains is violated require special attention and an analysis of the expected time of a possible collision (TCPA) as well as the speeds and courses of the ships against the background of historical data.

4.3 Anomaly Detection

In addition to the general movement pattern and behaviour analyses of ships, the potentials of anomaly detections of historical and current traffic and traffic movements are to be identified and examined using maritime traffic data. For example, strong course deviations can be investigated here, but also the abandonment of fairways, main shipping lanes or traffic separation areas due to large draughts. Anomaly detection offers the potential of an early intervention on the ship's command, for example to prevent collisions or groundings.

For the analysis of anomalies on the basis of course deviations within a defined area, the eastern section of the Kiel Canal is used. Based on this, an Isolation Forest (scikit-learn developers, 2018) provided by scikit-learn (Géron, 2018) will be used for outlier detection (Lewinson, 2018).
With the help of the trained Isolation Forest, an anomaly value is provided for each data point and displayed in color. In addition to the anomalies of specified areas, anomalies of routes can also be evaluated with the help of the Isolation Forest. If only position data and thus point densities are taken into account, unusual behavior of ships - such as slow-moving ships - cannot be detected. Conversely, fast sailing is more often regarded as unusual. In addition, in this case areas are marked as anomalies that are far away from the center of the point (e.g. in ports). For the training the input parameters latitude, longitude, speed as well as course over ground were used and an Isolation Forest returning an anomaly score for each data point the area of the Kiel Canal was trained. With a number of 1000 estimators, an accuracy of 90 % was achieved.
Collisions can be roughly divided into two categories: Collisions between two or more ships or the collision of a ship with an immovable structure such as offshore wind farms or bridges. For the detection of anomalies to prevent collisions, encounter situations can be evaluated with respect to the compliance of typical and thus normal evasive maneuvers of avoidable ships.
In a first step, encounter situations are extracted from the AIS data. For the extraction of these, the assumption is made that an encounter situation exists when the minimum distance of two ships in the same period on the open sea is less than 3 nautical miles. With the help of the trips described in section 3 and the CPA, all ship encounters and corresponding AIS messages

can be extracted. It has to be ensured that always the same times of two ships meeting each other are combined.

Based on the encounter data, the type of encounter situation is determined depending on the maneuver of the first moment. A distinction is made between the situations of frontal encounter, overtaking and intersection. In addition, the system detects which ship should initiate an evasive maneuver and which should maintain course and speed.

In order to determine the behavior of two ships encountering each other, a confidence interval of the speed and course change values of ships within the same area and considering the same encounter situations is then used. If μ_{TH} is the mean value of the course change rate, σ_{TH} the corresponding standard deviation and x_{TH} the course change rate of any evasive ship at the time of the assessment, then a normal evasive behavior exists for a significance level α if

$$x_{TH} \in \left[\mu_{TH} - z_{\left(1-\frac{\alpha}{2}\right)} \frac{\sigma_{TH}}{\sqrt{n}}; \mu_{TH} + z_{\left(1-\frac{\alpha}{2}\right)} \frac{\sigma_{TH}}{\sqrt{n}}\right],$$

with n being the number of observations and $z_{\left(1-\frac{\alpha}{2}\right)}$ the quantile of standard normal distribution.

4.4 Conclusion

To assess the feasibility of the AIS data analysis, the developed methods were validated on the basis of historical ship movement and environmental data and the values were checked for plausibility. With regard to methods that were developed using machine learning methods, the accuracy of these methods was also determined. It was found that the methods, especially the Isolation Forest for anomaly detection, used had good accuracy.

In addition to the potentials identified in the presented paper, the analysis and prediction of encounter situations between two or more ships can be used to determine the changes in speed and/or course of given encounter situations. In this context, neural networks and agent-based learning could be used to learn speed and course changes to avoid collisions. Deep learning methods can also be used for the surface and underwater detection of ships, coastlines or buoys and thus for object detection.

5 Limitations

It can be concluded that the identified potentials can be implemented within a system for business analytics on AIS data. With regard to a possible real-time implementation, the extraction of the mass data for motion pattern analysis and the offline training of the models in the case of anomaly detection must be taken into account.
In this context, it is also often necessary to take into account missing static ship data such as engine values or insufficient data storage capacities and computational powers. In addition, incorrectly captured values in the AIS and data consistencies result in an increased processing effort. Furthermore, especially in the context of machine learning algorithms, the loss of control as well as the lack of theory and the high degree of trial and error should be mentioned.
Despite the consistently provided data, they leave room for analysis within the human decision-making process, depending on the viewer. In the course of a real-time online tool, the topic of data security must also be taken into account as well.

6 Perspectives and Outlook

According to the port and water authorities, up to 30% efficiency savings can be achieved through automated analysis of movement data. In addition, the number of direct connections and transshipments can be determined for shipping companies and ship owners in particular or to determine congestion issues of ports and terminals. In this context, efficiency gains can be achieved through the selective retrieval of relevant information or complete situational awareness from a single source. There is the possibility that further or more precise outputs could improve the processes or expand the planning horizon, since the available information is currently considered and evaluated separately. Apart from this information, conclusions on the speed of port operations of different shipping companies can be discussed, berth availabilities or schedule integrities can be determined to extend the planning horizon of maritime stakeholders.

Since 01.01.2018, the obligation to report CO2 emissions is mandatory for ships travelling to and from Europe as well as for intra-European traffic. In this context, the first emission report has to be delivered by 30.04.2019 to the EU. The amount of CO2 emitted must be transmitted for the entire voyage, from the port of departure via European ports to the port of destination. In order to meet these requirements and to enable and provide the maritime stakeholder with performance monitoring of fuel consumption and associated emissions, Fraunhofer CML together with the Wismar University of Applied Sciences, the JAKOTA Design Group, the German Aerospace Center (DLR) and the project manager JAKOTA Cruise Systems is developing a software prototype for calculating CO2-emissions within the project EmissionSEA. The data of the ships are used as well as information

from the weather service to derive fuel consumption and emissions from speed and external influences. These assessments can also be used to draw conclusions about compliance with slow steaming measures.
In addition, CML is planning a follow-up project based on the results of the potential analysis presented within the paper containing the technical implementation and development of a suitable software solution for the interactive analysis of the above-mentioned data.

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Current State and Trends in Tramp Ship Routing and Scheduling

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Purpose: This paper discusses the current state of routing and scheduling in tramp shipping, an important planning problem on the operational level in maritime logistics. The purpose is to report and compare the existing methods and to investigate possible future additions and improvements. Furthermore, an outlook on potential applications of machine learning for this optimization problem is given.

Methodology: In this paper an extensive literature review of reports and journal papers on cargo routing in tramp shipping of the last seven years is conducted. The wide range of findings are categorized by the different considered characteristics. The results are analyzed and trends are pointed out.

Findings: Optimization problems in tramp shipping differ in their main properties from liner shipping or classical vehicle routing problems. Thus, different approaches and implementations are required when developing or adapting existing optimization algorithms. The real-world problem is often limited in the optimization, so found solutions are improvements, but cannot fully reflect reality yet.

Originality: This paper provides a comprehensive overview of tramp ship routing and scheduling. Although optimization of routing and scheduling in liner shipping is fairly well researched, the publications on tramp shipping are sparse in comparison. This leaves room for future research, as the findings for liner shipping and vehicle routing are not directly applicable to tramp shipping.

Keywords: Tramp Shipping, Routing and Scheduling, Maritime Transportation, Cargo Routing

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1 Introduction

The global volume transported on sea in 2018 was 10.7 billion tons, 53.5% of which was bulk cargo and 29.4% oil and gas (UNCTAD 2019). As these cargo types are mainly transported in tramp ship mode, the significance of tramp shipping in the world trade becomes apparent. Since the competitive pressure among tramp shipping companies is high, savings through targeted planning of routes and schedules are an enormous competitive advantage. The objective of this paper is to report and compare the existing methods to the tramp ship routing and scheduling problem (TSRSP) and to identify possible future research directions. An additional outlook on potential applications of machine learning for the TSRSP is given.

In general, commercial cargo shipping is differentiated into three basic modes: liner shipping, tramp shipping and industrial shipping. In the liner mode, ships travel according to published time tables and transport cargo on the associated routes, comparable to a bus line. In tramp shipping the vessels follow the available cargoes. Sticking with the analogy, this transport mode can be compared to a taxi service. Operators in liner shipping as well as tramp shipping aim to select a route and schedule for each ship in order to maximize their profit. In industrial shipping, where the operator owns cargoes and ships, the operator tries to minimize their costs (Christiansen et al. 2007). In recent years, a shift from industrial shipping to tramp shipping could be observed (Christiansen, Fagerholt & Ronen 2004; Christiansen et al. 2013). As tramp shipping and industrial shipping both have the optimization problem of cost reduction or profit maximization by transporting spot cargoes additionally to the mandatory cargoes, industrial shipping is treated as a sub-problem of tramp shipping in this paper.

The optimization problem of tramp shipping differs in its main properties from liner shipping or classical vehicle routing problems. One of the main differences of maritime transportation and transportation on land is that ships usually operate 24 hours a day and under all weather conditions which leads to a high planning uncertainty. In addition, the demand tends to be more dynamic compared to the static planning of schedules in liner shipping (Christiansen et al. 2004). Thus, different approaches and implementations are required when developing or adapting existing optimizations. As ships operating in tramp shipping do not necessarily have a home depot, the definition of a planning period is often time and not location-dependent. This leads to cases where a planning period finishes while ships of a tramp fleet are still on voyage. The length of planning horizons varies greatly over the reviewed publications depending on whether a short-sea or a deep-sea problem was investigated. Naturally deep-sea planning problems have longer planning horizons compared to short-sea planning problems, as the travel times are considerably longer. The optimization problem of the TSRSP is often limited, so the found solutions are improvements, but cannot fully reflect reality yet.

Since the research interest in the field of TSRSP is growing steadily, more articles on the TSRSP have been published in the recent years. In the past, several literature reviews on ship routing and scheduling have been published (Ronen 1993; Christiansen et al. 2004; Christiansen et al. 2013). This paper aims at taking a similar perspective on the topic while taking the latest publications into account.

This paper is organized as follows: a problem definition as a general mathematical formulation is given in Section 2. In Section 3, different solutions and approaches for the TSRSP are categorized and presented. Section 4 provides a brief analysis of the reviewed literature. The last section contains the concluding remarks and points out possible future research directions.

2 Problem Definition

For a better understanding of the complexity of the TSRSP as an optimization problem, a mathematical formulation of the basic TSRSP presented by Christiansen et al. (2013) is repeated here. Optional spot charters of ships are included in order to describe the basic optimization problem on which many publications are based. Although, short-sea shipping and deep-sea shipping have very different topologies and thus different planning horizons, this mathematical approach is valid for both. The set of vessels in a fleet is denoted by V and each ship by the index v. The index n denotes the number of cargoes in the planning horizon. Each cargo or node is indexed with i. The set of pick-up nodes or cargoes is described by $N^p = \{1,2, \dots, n\}$ and the set of delivery nodes by $N^D = \{n+1, n+2, \dots, 2n\}$ correspondingly. The set N^P is divided into a set of contract cargoes N^C and a set of optional spot cargoes N^O. A network is formulated as (N_v, A_v) where N_v is a set of nodes which can be visited by a vessel v, including the artificial origin and destination $o(v)$ and $d(v)$. While the artificial origin can be any point at sea or in a harbor, the destination is defined by the found solution and matches the last delivery harbor of vessel v. The set of feasible arcs for a vessel v is denoted by A_v. Thus, the set of feasible pick-up nodes for a vessel v is $N_v^p = N^p \cap N_v$ and the set of feasible delivery nodes is $N_v^D =$

$N^D \cap N_v$ accordingly. The quantity of cargo i is represented by Q_i and capacity of a vessel v is represented by K_v. The sailing time of vessel v between nodes i and j is indicated by T_{ijv}. The time window at a node i is denoted by $\left[\underline{T_i}, \overline{T_i}\right]$ with the start time $\underline{T_i}$ and the end time $\overline{T_i}$ respectively. Let R_i be the revenue for cargo i and C_{ijv} the transportation costs of vessel v between nodes i and j. Christiansen et al. (2013) define the transportation cost C_{ijv} as sailing costs and port costs at node i, though different models and approaches define the cost differently. The time at which the service on vessel v at node i starts is t_{iv} and l_{iv} denotes the load onboard of ship v after the service at node i has ended. The binary flow variable x_{ijv} indicates whether a vessel v sails from node i to node j ($x_{ijv} = 1$) or not ($x_{ijv} = 0$). This results in the following formulas:

$$\max \sum_{v \in V} \sum_{(i,j) \in A_v} (R_i - C_{ijv}) x_{ijv} \tag{1}$$

s.t.

$$\sum_{v \in V} \sum_{j \in N_v} x_{ijv} = 1, \qquad i \in N^C \tag{2}$$

$$\sum_{v \in V} \sum_{j \in N_v} x_{ijv} \leq 1, \qquad i \in N^O \tag{3}$$

$$\sum_{j \in N_v} x_{o(v)jv} = 1, \qquad v \in V \tag{4}$$

$$\sum_{j \in N_v} x_{ijv} - \sum_{j \in N_v} x_{ijv} = 0, \quad v \in V, i \in N_v \backslash \{o(v), d(v)\} \tag{5}$$

$$\sum_{i \in N_v} x_{id(v)v} = 1, \qquad v \in V \tag{6}$$

$$x_{ijv}\left(l_{iv} + Q_j - l_{jv}\right) = 0, \qquad v \in V, j \in N_v^P, (i,j) \in A_v \tag{7}$$

$$x_{i(n+j)v}\left(l_{iv} - Q_j - l_{(n+j)v}\right) = 0, \qquad v \in V, j \in N_v^P, (i, n+j) \in A_v \tag{8}$$

$$0 \leq l_{iv} \leq K_v, \qquad v \in V, i \in N_v^P \tag{9}$$

$$x_{ijv}(t_{iv} + T_{ijv} - t_{jv}) \leq 0, \qquad v \in V, (i,j) \in A_v \qquad (10)$$

$$\sum_{j \in N_v} x_{ijv} - \sum_{j \in N_v} x_{(n+i)jv} = 0, \qquad v \in V, i \in N_v^p \qquad (11)$$

$$t_{iv} + T_{i(n+i)v} - t_{(n+i)v} \leq 0, \qquad v \in V, i \in N_v^p \qquad (12)$$

$$\underline{T_i} \leq t_{iv} \leq \overline{T_i}, \qquad v \in V, i \in N_v \qquad (13)$$

$$x_{ijv} \in \{0,1\} \qquad v \in V, (i,j) \in A_v \qquad (14)$$

The goal is to maximize the revenue in objective function (1) under the constraints (2) – (14). Sometimes, especially in industrial shipping, the objective function is defined to minimize the overall costs (e.g. Hemmati et al. (2014), Christiansen et al. (2007), Gatica & Miranda (2011), Wen et al. (2016)). The transportation requirement for the mandatory contract cargo is given in constraint (2), the requirement for the optional spot cargo is given in constraint (3). The sailing route of a vessel is defined by constraints (4) – (6). In constraint (7) and (8) the shipload onboard a vessel at each pick-up and delivery node is documented. Constraint (9) guarantees the load does not exceed the capacity of a vessel v. Constraint (10) describes the compatibility between schedules and routes for a vessel v. Constraint (11) ensures the vessel which visited the pick-up node also visits the corresponding delivery node, while constraint (12) keeps the visits in the correct order, meaning no delivery node can be visited prior to its corresponding pick-up node. The time window at a node i is defined by constraint (13). As prior mentioned, the binary variable x_{ijv} is listed in constraint (14). The combination of restrictions paired with the amount of ships and cargoes in a TSRSP, makes the routing and scheduling in tramp shipping a complex optimization problem. The TSRSP is a NP-hard problem (see Lin & Liu (2011)) and thus often solved using heuristic approaches.

3 Solutions to the TSRSP

As prior mentioned, the model for TSRSP is not uniformly defined, leading to different approaches and therefore to different solutions. Various treatments of initial ship locations or for shiploads (full-shipload, less-than shipload or mixed shipload) and diverse assumptions for example on costs or cargo constraints, make it difficult to compare approaches and solutions to the TSRSP directly. This section attempts to sort the various solution approaches to the TRSRSP according to their focus area in order to provide a good overview of the current state of research.

Hemmati et al. (2014) present benchmark instances and a benchmark generator for tramp ship routing and scheduling problems with the goal to provide test instances representing realistic planning problems. The benchmark generator is applicable to short-sea and deep-sea voyages, full-shiploads or mixed shiploads. The authors aim to provide a basis for future development of better solution algorithms, thus each presented instance includes the best known solutions for the instance specific TSRSP. Solutions are generated using a commercial mixed-integer programming solver for small-scale instances and a large adaptive neighborhood search (ALNS) heuristic for large-scale instances. The following restriction is applied when calculating the solutions: all ships sail with a fixed speed in a heterogeneous fleet with the options of spot charters.

3.1 TSRSP with Variable Speed

Several approaches in solving the TSRSP include a speed optimization or variable speeds in order to reduce fuel consumption and as a positive side effect emissions and thus increase the overall profit of a tramp fleet. A simple mathematical model for including speed optimization in the TSRSP is provided by Fagerholt & Ronen (2013), who prove the benefits of speed optimization. Approaches with speed optimization or variable speeds are presented in more detail in this section.

The work of Castillo-Villar *et al.* (2014) is based on the model of Gatica & Miranda (2011), who introduced variable speed to a TSRSP. In the approach of Castillo-Villar *et al.* for a ship routing and scheduling problem with variable speed and discretized time windows it is assumed all cargo is known at the beginning of each planning period, thus there is no distinction between spot and contract cargoes. A heuristic based on a variable neighborhood search algorithm is proposed to solve the test instances. The values for speed and the discrete time windows are fixed in the test instances. As the results are compared to exact solutions generated with the solver CPLEX, only instances where CPLEX was able to find solutions are considered. The optimal gap to the optimal solutions is 6% to 8%. The authors do not compare their found solutions to the ones of Gatica & Miranda, so no statement on possible improvements can be made.

Wen et al. (2016) presented a branch-and-price approach for solving the TSRSP with variable speeds. To reduce the time needed for computational calculations infeasible routes are removed beforehand. A heterogeneous fleet with different speed ranges depending on the individual vessel with the following restrictions is considered: ships can either sail in ballast or in laden and other operating costs than fuel consumption (e.g. crew or maintenance costs) are neglected. The authors vary the fuel price in the calculations, resulting in the finding that the fuel price has significant influence on the calculated speed and amount of transported cargoes. Wen et al. (2016) show that while the sailing speed is often contractually agreed between ship owner and cargo owner, allowing speed variation could improve the profit and the amount of transported cargoes. Although the approach of Wen et al. (2016) is similar to the one of Gatica & Miranda (2011), one significant difference is the calculation of the fuel consumption. While the latter only considers the sailing speed as a factor for the fuel consumption, Wen et al. (2016) calculate the fuel consumption as a function of ship-load and sailing speed.

To optimize the sailing speed for tramp ships Yu *et al.* (2017a) proposed a fast elitist non-dominated sorting genetic algorithm (NSGAII). The goal is to optimize the sailing speed under two aspects: minimization of the operation costs for the tramp shipping company, the carrier, and maximization of the satisfaction of the cargo owner, the shipper. The shipping costs are assumed to be only speed dependent, reducing the total costs to the cost of the fuel consumption, which can be lowered by reducing the sailing speed. The service satisfaction of the shipper is measured using fuzzy time windows, since it is assumed the satisfactions decreases with deviation from the desired delivery time. As the ship routes and transported cargoes are known beforehand and thus spot and contract cargo are not distinguished, Yu *et al.* do not investigate a typical TSRSP. Nonetheless, the found results are of interest, as they confirm the tradeoff between low shipping costs for the carrier, and on time delivery for the shipper.

3.2 TSRSP under Environmental Aspects

In 2018 the International Maritime Organization (IMO) adopted an initial strategy to reduce the greenhouse gas emissions. The goal is to reduce the total emissions by 50% compared to the reference year 2008 (IMO 2018).

Together with the growing environmental awareness in society, tramp shipping companies are under pressure to adapt to more environmentally friendly transportation.

Wang et al. (2019) investigate the influences of two market-based measures for CO2 reduction on operational decisions in a TSRSP with variable. They used the mathematical model presented in Section 2 extended by constraints for variable speed and charter in-options. The impacts of a bunker levy, similar to a carbon tax on profit, on average travel speed, on the amount of served cargoes as well as on the emissions are evaluated. The fuel consumption rate FC of a vessel is defined as a function of its speed s and its payload p, where A, B and C are ship-specific empirical parameters.

$$FC = (A \cdot s^2 + B \cdot s + C) \cdot (0.8 + 0.2 \cdot p) \tag{15}$$

In the bunker levy scheme, an additional tax is charged on every ton of consumed fuel. The resulting costs are subtracted from the revenue function. Test instances based on the benchmark suite of Hemmati et al. (2014) are used to investigate the bunker levy scenario further. A commercial routing and scheduling software developed by the Norwegian Marine Technology Research Institute is used to solve the instances. The authors conclude that with increasing levies and/or fuel prices, the profit, the average travel speed, the amount of served cargoes and the CO2 emissions decrease. As Wang et al. focus on the operational planning horizon, the influences of market-based measures for CO2 reduction on strategical planning are unknown.

Furthermore, the publication of Wen et al. (2017) on a general ship routing problem with speed optimization for either liner or tramp shipping should be mentioned. They considered fuel consumption as a function of ship payload and include fuel price, freight rate and costs of in-transit cargo in order to calculate the total transportation cost with the goal to minimize the costs and thus minimize the emissions. Their test instances are solved using a branch-and-price method or a constraint programming model.

3.3 TSRSP with Extended Cargo Constraints

While most approaches to the TSRSP consider basic cargo constraints, such as deadweight restrictions of a ship, other approaches go into more detail and consider several ship restrictions or different approaches such as cargo coupling or split-loads. Considering more details leads to solutions which can reflect reality more closely, as Fagerholt & Ronen (2013) show in their publication on the basis of a TSRSP with split-loads and a TSRSP with flexible load sizes.

Fagerholt et al. (2013) look into the routing and scheduling problem of project shipping. Project shipping is considered a sub segment of tramp shipping, as cargoes tend to be more unique, e.g. parts of machinery or wind turbine blades. These cargoes lead to tougher requirements regarding the stowage onboard and more precise stowage constraints are introduced. Additionally, the authors include cargo coupling constraints. Some cargoes are coupled and can be solely accepted or rejected as a set and thus have to be evaluated as a sfithough the constraints regarding stowage and cargo coupling are fairly detailed, Fagerholt et al. neglect the deadweight restrictions of ships. They solve the TSRSP using a tabu search heuristic, which has been implemented in a tool for shipping companies (see Fagerholt 2004). The results are compared to exact solutions and show a good solution quality.

Stålhane et al. (2014) are the first to introduce Vendor Managed Inventory (VMI) to a TSRSP. According to their research replacing the standard Contract of Affreighment (CoA) with VMI could lead to combined economic benefits for charterers and tramp shipping companies. The transport conditions of most contract cargoes in tramp shipping are defined in a CoA, which defines the amount of cargoes to be transported in a fixed time frame between defined ports. Usually the payment per ton, but not the amount of cargo per ship is agreed upon in a CoA (Stopford 2003). VMI has the opportunity to introduce more flexibility in cargo quantities and delivery times and could improve the whole supply chain. The authors develop a hybrid approach with a priori path generation of all feasible routes and a branch-and-price network which generates the schedules dynamically to solve the basic TSRSP with VMI. The results are compared with exact route generation instead of the proposed heuristic route generation. Stålhane et al. conclude that the VMI could increase the profit for tramp shipping companies significantly, especially if the market is poor and few spot cargoes are available, although the realization of VMI in the tramp market is questionable.

Hemmati et al. (2015) develop a method to solve realistic scaled instances based on the preliminary work of Stålhane et al. (2014). They introduce a two-phase heuristic, which first converts the inventories into cargoes. The routing and scheduling problem is then solved using an ALNS method. In order to reduce the computing time, feasible combinations are clustered by a k-means algorithm and subsequently solved using the ALNS algorithm. In the second phase the solution is analyzed, then the cargoes are updated, and an iteration process is started. Using the described heuristic, Hemmati et al. achieve shorter computational times and show that the benefit of VMI depends on the fleet composition, the number of spot cargoes available, and the amount of contracts converted to VMI.

Besides Fagerholt et al. (2013), Stålhane, Andersson & Christiansen (2015) also investigate project shipping with cargo coupling and include synchronization constraints in addition. Synchronization constraints define restrictions with regard to delivery times of the first and the last cargo of a set. A branch-and-price method is used to solve the routing and scheduling problem. The results are benchmarked against the ones of Andersson, Duesund & Fagerholt (2011), as the same test instances are used. The authors prove a bench-and-price algorithm reduces the computational time. They conclude that large-scale instances in project shipping are simpler to solve than for example in regular tramp shipping, as the cargo ship capability restrictions are stricter, leaving less feasible cargoes.

3.4 TSRSP with Bunkering Decisions

The tramp ship routing and bunkering problem is a niche problem in the TSRSP, but no less important. The fuel consumption causes the main variable costs of a tramp ship voyage, therefore a bunkering strategy and buying fuel cheaply can lead to a competitive advantage.

Vilhelmsen, Lusby & Larsen (2014) investigated the influence of integrating bunkering decisions in the TSRSP in order to maximize the profit. They consider spot and contract cargo with the following restrictions: ships can sail either in ballast or full shiploads and each ship sails at the most economic, most cost-efficient speed. Thus, ship speed as well as costs are calculated dependent on the shipload. A dynamic column generation is used to solve the TSRSP with bunkering decisions. The developed solution is tested on instances with variable percentage of spot cargo and different bunker prices. Vilhelmsen et al. (2014) discover that the fluctuations of bunker prices have the most effect on instances with a high percentage of spot cargo, as contract cargo has too many restrictions to choose from different ports to bunker.

Meng, Wang & Lee (2015) examine the TSRSP under the goal to determine the amount fuel to bunker at each port in order to maximize the profit using a branch-and-price method. Although the approach is similar to Vilhelmsen et al. (2014), several differences can be pointed out. Meng et al. assume fixed travel speed and do not allow detours for bunkering. Solely loading and unloading ports can be used for bunkering. The test instance are randomly generated.

Although Besbes & Savin (2009) do not study the classical TSRSP (according to the definition in Section 2), their groundwork for refueling decisions in liner and tramp shipping are worth mentioning here. They included stochastic bunker prices which creates further complexity in optimal routing decisions. Therefore, concerning tramp shipping the authors investigate a single ship and not a fleet with deterministic sailing time between ports and consider only spot cargoes.

3.5 TSRSP under Uncertainties

Maritime operations are subjected to different kind of uncertainties, which affect routing and scheduling of ships. Examples for such uncertainties are weather factors, cargo demand, or waiting time for berth at harbors. Some authors include uncertainties in the TSRSP to improve the overall quality of routing and scheduling in tramp shipping.

Guan et al. (2017) take uncertain time windows in the TSRSP into account. They conduct a survey on the waiting time of ship for berth and focused their study on harbors with a large export volume. Neither the definition for waiting time on berth nor the quantification for large export volume is given which results in a lack of clarity and preciseness. Guan et al. use a column generation algorithm to solve large-scale test instances with a homogeneous fleet and fixed speed. The information generated from the survey combined with the time a ship owner is willing to spend waiting for berth is used to generate and assess random waiting days for each test instance. The aim of this publication is the classification of ships in the fleet into three categories: (1) long time charter, (2) short time charter and (3) no further decision at the current point of time.

Yu et al. (2017b) take two uncertainties into account while solving the TSRSP. First, Seasonal fluctuations of demand are considered in the form of freight rates, which change every three months in the test instances and thus influence the profit of a tramp shipping company. Second, weather conditions are included in form of statistics. Yu et al. permit the possibility of discarding contract cargoes under a penalty factor in order to maximize the profit during a planning period. This is a questionable choice in practice, as a tramp shipping company could damage their reputation beyond the planning horizon by abandoning contract cargoes. A genetic algorithm is applied in order to solve different test instances with static cargo demand and uncertain cargo demand in form of additional available cargoes during the planning horizon. The profit increases with decreasing penalties for discarding contract cargoes and static cargo demand, which is to be expected. Yu et al. do neither compare their results to an exact solution nor to real-life data.

By including a choice inertia of cargo owners, Zhao & Yang (2018) try to eliminate one uncertainty in tramp shipping. The authors assume that the past decisions of cargo owners remain in their memory and will affect current decisions when choosing a tramp shipping company on the spot market. The market share of a tramp shipping company on a segment between two ports is calculated by a logit model and based on the size of the company and the number of completed voyages on this specific segment. Zhao & Yang include quarterly fluctuations of the freight rate as a function of the sailing distance and a seasonal factor, which was found using data fitting based on the Baltic Dry Index of 2015. To solve the TSRSP, a genetic algorithm is used. The influences of the choice inertia and of the fluctuations in the freight rate are tested in a test case with a homogeneous fleet and fixed sailing speed considering only spot cargoes. The found results include more than 40% ballast voyages for each ship in the planning horizon of one year. The authors conclude from these results that ballast voyages pay off by securing a greater market share on a specific segment between two ports when looking at the whole planning period.

3.6 TSRSP with Miscellaneous Extensions

In this section several approaches on solving the TSRSP, which do not fit in the previous presented categories, are listed.

An uncommon approach to the TSRSP is chosen by Moon, Qiu & Wang (2015) in form of a hub-and-spoke-network for container ships. Usually container ships operate in liner shipping mode, which might not be economically profitable for ultra large container ships (ULCS) with more than 10.000 TEU capacity. In order to fully utilize a ULCS, the authors suggest that feeder container ships travel between spokes and hubs in order to collect cargoes for ULCS, which travel between hubs. To create a network design as well as solving the TSRSP, a genetic algorithm is used. In each test instance all demands are known beforehand, all cargoes have to be transported and time windows are neglected. The results show a significant reduction of the computing time with equally good results compared to the solver CPLEX.

Armas et al. (2015) adopted the modeling approach of Gatica & Miranda (2011) and also the one of Castillo-Villar et al. (2014) without variable speed. They proposed a hybrid heuristic consisting of a greedy randomized adaptive search procedure to find initial feasible solutions and a variable neighborhood search, which is used to improve the found solutions. Armas et al. (2015) compare their results with the ones of Castillo-Villar et al. (2014), as they neglect the variation of speed in their test instances. Additionally, the found solutions are benchmarked against exact solutions. The solution quality and computing time could be improved significantly, but both depend on the level of discretization of the time windows.

Vilhelmsen, Lusby & Larsen (2017) investigate the TSRSP with voyage separation requirements. These ensure a time-wise evenly-spread of similar voyages, which is a common requirement in CoAs. They presented a mixed-integer programming formulation consisting of a dynamic column generation algorithm and a branch-and-price method. The authors assume fixed speeds for full shipload and ballast cases in all test instances. The results show that including voyage separation requirements has a minimal negative influence on the profit, but can represent reality more closely.

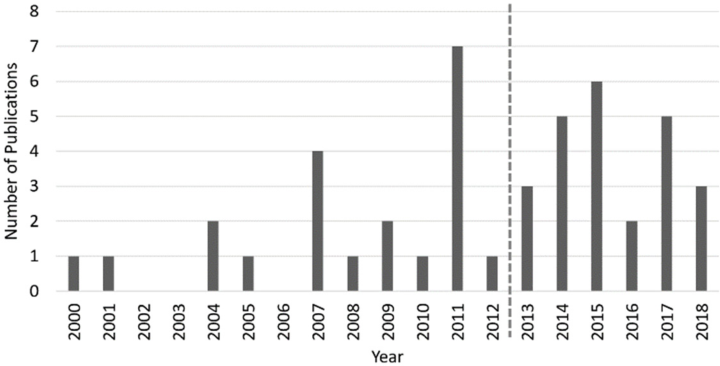

Figure 1: Publications on the TSRSP since 2000, including grey literature

4 Methodology and Analysis of the Literature Review

This section aims to describe the methodical approach of literature search and to analyze the reviewed publications. Similar restrictions as in prior literature reviews (see Section 1) are applied: this review includes literature focusing on cargo routing in tramp shipping published from 2013 until May 2019 in English in refereed journals, books, or conference proceedings. Online search tools (e.g. "Scopus", "Google Scholar") were used to search for the terms "routing", "scheduling", and "tramp shipping" or variations thereof. During the search process the snowballing technique in which new publications are discovered by searching the references of relevant papers was applied (Booth, Sutton & Papaioannou 2016).

Figure 1 illustrates the increase in publications fitting the search criteria since 2000, publications from 2019 are omitted in this Figure, since the year is ongoing. The dashed line marks the lower time limit set in this paper. This overview includes unreviewed publications. The increase in publications is related to the cost pressure associated with the shipping crisis, as well as rising crude oil prices. Although the search has been carried out thoroughly, it cannot be ruled out that individual publications may have gone unnoticed. Since the literature analysis is limited to a period of less than seven years, long-term trends cannot be detected.

Table 1: Test Instance Parameters by Publication

Publication	**Planning Horizon in Days**	**Number of Ships**	**Number of Cargoes**
Wang et al. (2019)	-	6 to 20	25 to 50
Zhao and Yang (2018)	365	6	-
Guan et al. (2017)	300 to 360	17	94
Vilhelmsen, Lusby and Larsen (2016)	90 to 150	10 to 32	4 to 13
Wen et al. (2017)	-	3	6 to 31
Yu et al. (2017)	-	1	4
Yu, Wang and Wang (2017)	365	5 to 25	500
Wen et al. (2015)	30 to 90	20 or 32	40 to 160
Armas et al. (2015)	-	4 to 7	30 to 50
Hemmati et al. (2015)	-	4 to 8	10 to 30
Meng, Wang and Lee (2015)	-	20 or 40	20 to 60

Publication	Planning Horizon in Days	Number of Ships	Number of Cargoes
Moon, Qui and Wang (2015)	-	-	-
Stålhane, Andersson and Christiansen (2015)	-	3 or 4	10 to 32
Stålhane et al. (2014)	-	4	6 to 15
Christiansen and Fagerholt (2014)	-	-	-
Hemmati et al. (2014)	-	3 to 50	7 to 130
Vilhelmsen, Lusby and Larsen (2014)	30 to 60	7	30 to 60
Castillo-Villar et al. (2014)	-	4 to 7	30 to 50
Fagerholt et al. (2013)	-	2 to 8	6 to 63

For a brief overview on the reviewed literature, the different parameters of test instances by publication are listed in Table 1. If the planning horizon is not fixed, the element in the Table is marked with a dash ("-"). The size of test instances for each proposed solution for the TSRSP varies greatly, depending on problem definition and the used data. This makes a comparison of the solution quality and applied

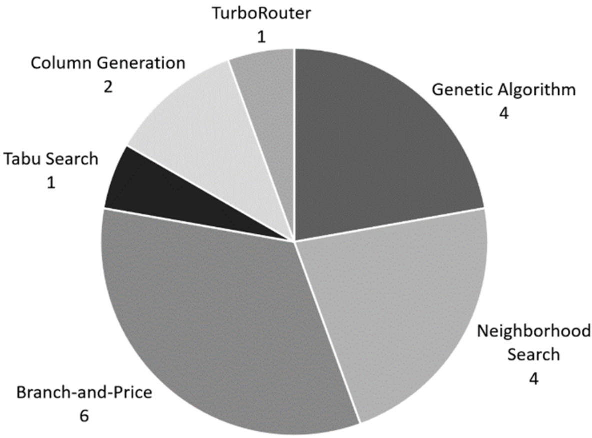

Figure 2: Quantitative comparison of the used methods respective solvers

algorithms impossible, e.g. larger test instances tend to require more computing time and are generally more difficult to solve. An overview of the methods used to solve the TSRSP in the presented publications is shown in Figure 2. This comparison of the ratios of each algorithm type aims to demonstrate the common applied algorithms. The branch-and-price method is used in six of the reviewed publications and the most popular, as its combination of column generation and branch-and-bound algorithm leads to short computing times. A trend wave of using genetic algorithms to solve the TRSRSP is observed, as all reviewed publications using genetic algorithms have been published between 2015 and 2017.

5 Outlook and Concluding Remarks

An extensive literature review of reports and journal papers on tramp ship routing and scheduling of the last seven years is conducted. The wide range of findings is categorized by the different considered problem characteristics and an overview on the current state of research is provided. This section recaps and presents future research directions.

A general trend in publication on the TSRSP is the use of randomly generated data. The use of artificial data can be attributed to the lack of real-life data, but implies the risk of developing impractical solutions for real-world problems. Although instance generators are provided (see Hemmati et al. 2014), without real-life data no statements about actual improvements in the day-to-day planning business can be made. A continuous trend is simplification of mathematical models, which are certainly easier to solve but far from real conditions as Fagerholt & Ronen (2013) state. Psaraftis (2019) sees possible future improvements if the focus is shifted from the development of solution methods to modeling processes of the real-world problem. An increase in applications of machine learning methods as a solver to the TSRSP can be observed, but leaves still room for further research directions.

The stowage onboard is crucial for the ship stability and hence for the safety of crew and environment. The solution with the greatest profit does not necessarily have to meet the legal requirements of ship stability, but this is rarely taken into account. Introducing stability constraints regarding cargo could lead to more realistic solutions of the TSRSP in future research. Another open question is how a cargo priority scheme which goes beyond the classification of spot and contract cargo can be formulated.

A few publications include seasonal fluctuations of demand or patterns in freight rates, although these affect the revenue in tramp shipping business directly. Future studies on not only seasonal, but also geographical fluctuations could improve and raise the operational TSRSP to a tactical level. With better knowledge on seasonal and geographical patterns, tactical ship allocation to regions or decisions on charter contracts can be made more effective. Further research needs to investigate how waiting times for berthing influence the profitability of cargoes. Since available real-life data on TSRSP is limited, a higher data accuracy or a larger amount of data can be achieved through the additional use of data from the Automatic Identification System (AIS). AIS data enables researchers to predict travel times on specific routes, which enables improved speed prediction and thus leads to a better assessment of fuel consumption. This opens up new opportunities for tramp shipping companies, as they are able to select cargoes based on more exact forecast of shipping costs.

In summary, the TSRSP offers many opportunities and possibilities for further research and improvement on a methodical as well as on a practical level.

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Fleet Based Schedule Optimisation for Product Tanker Considering Ship's Stability

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Purpose: Scheduling a fleet of product tankers in a cost effective and robust way to satisfy orders is a complex task. A variety of constraints and preferences complicate this attempt. Manual solutions as common in tramp shipping are not sufficient to deliver optimal and robust schedules.

Methodology: For this, we present a mixed integer linear programming formulation of the scheduling problem. Additionally intact stability calculations for each ship of the fleet are implemented in a separate program that checks the feasibility of MILP solutions and creates new cuts for the integer program.

Findings: Usually the checking of the stability criteria is done before an order will be accepted and the schedule of the ship is planed accordingly. This requires the selection of a ship a priori. Checking the admissibility of a voyage gives access to a wider variety of possible combinations.

Originality: To our knowledge fleet scheduling under consideration of intact stability requirements has received little attention in the literature. Previous works make very simple assumptions on the capacity of the ships and do not include in their linear pro- grams any stability models.

Keywords: Cargo Scheduling in Tramp Shipping, Optimization, Ship Stability, Mixed Integer Linear Programming

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1 Introduction

Shipping even if not obvious is one of the most important industries with a big impact in our everyday life. Around 90% of the world trade is transported by the shipping industry (Ronen, 2019). Deep-sea shipping is the only way for transportation of a large amount of goods over the world. For many countries shipping belongs to one of their key industries. The financial crisis 2007 has changed this industry drastically. The reduction of profit margins on one side and the vessel as a huge capital investment for a shipping company with thousands of dollars daily total operation costs on the other side have increased the focus on optimization for cost savings. The efficiency of fleet schedules has a significant financial impact for the company.

Tramp shipping as described in (Lawrence, 1972) is one of the three main modes of maritime operations which include additionally industrial and liner shipping. Tankers usually do not follow fixed itineraries as container ships. They travel according to customers' orders and needs and are very often compared with taxi services. Shipping companies have long- term contracts as well as spot cargoes. The main aim of shipping companies working in this mode is to maximize their profits by appropriately scheduling and routing the fleet for the long-term contracts which implicitly limit the choice of spot cargoes.

Scheduling a fleet of product tankers in a cost effective and robust way to satisfy as many orders as possible is a complex task. This challenge can be defined as the problem of allocating the right assets to the right cargoes, such that all orders are delivered on time, at the right ports and by taking into account customer preferences as well as legislative requirements.

These requirements vary from minimum age of the ship to its vetting records. A robust scheduling and routing of the long term contracts has a direct impact on the online scheduling problem of assigning spot cargoes to ships. In this paper the focus will be on scheduling long-term orders in an optimal way under consideration of cargo, port and especially fleet and ship stability requirements. This problem is also known as the problem of cargo routing based on the classification and descriptions made in (Al-Khayyal and S.-J. Hwang, 2007). In contrast to this, in the inventory scheduling problem the cargo demand is determined by the schedules.

Nowadays in the shipping companies the very time consuming task of fleet scheduling is done manually and based on planners' experience. This process as described in (Trottier and Cordeau, 2019) and also confirmed during an interview with a tanker shipping company from Hamburg is a very iterative, manual and difficult one. Basically, the planners try to assign the mandatory orders first and then fill up the gaps with spot cargoes in a profitable way.

Obviously it is impossible even for a very small fleet to create optimal schedules in a manual way such that all constraints and requirements are taken into consideration. The suboptimal manual solutions lead to dead locks in the assignments of orders due to the lack of robustness or to a relatively high number of idle days and therefore to considerable financial loss. Safety and security are relevant for all mode of maritime transportation, but specially tanker ships have to fulfill high standards and requirements in security, which affect directly the company operations. Ship stability is at this point of high relevance and needs to be considered when optimizing the schedules in order to guarantee safety and save costs and reputation loss due to accidents. Nowadays this process is done also in a manual way and involves the engineering department that checks individual solutions proposed by the chartering department and revokes them if the stability of the ship is not guaranteed. The main aim is to schedule a given fleet in such a way that it delivers as much cargo as possible as a whole by maximizing the profit and on the same time complying with all cargo and ships stability requirements and restrictions. The problem is formulated as a mixed integer linear problem (MILP) with lazy constraints being generated by a separate module that calculates the stability of each ship given the cargo load from the MILP, as shown in Figure 1. Including this step in the optimization leads to more realistic results then existing MILP formulations, that are limited only to draft restrictions for ports and do not take ship design into consideration. Numerical experiments have shown that a large number of feasible solutions of the MILP do not comply with the stability requirements. A detailed description of the problem with all constraints and the mathematical formulation for the MILP and ships stability calculation can be found in section 3.

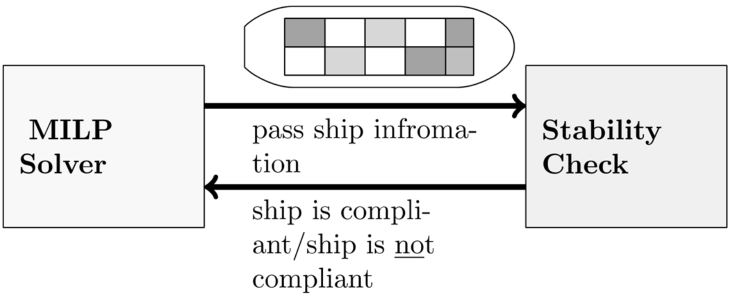

Figure 1: Program interaction

This paper is organized as follows. In section 2 the relevant literature is presented. The problem is described in detail in section 3. In section 4 first numerical experiments are presented and their results are analyzed. Concluding remarks and future work can be found in section 5.

2 Literature Review

Optimization models and methods for ship routing and scheduling problems are relatively new for this old and traditional transportation industry. Thus problems are considered to be complex and not easy to classify and solve. In comparison to air, train or public transportation shipping is characterized by a high uncertainty in the voyage and cargo information, which limits the usage of deterministic models. Nevertheless in the last years a significant growth in the number of scientific publications in this field has been recognized. The problem of ship routing and scheduling presented in this paper is considered as a special case of the general vehicle routing problem, see (Desrosiers et al. 1995). Methods and formulations used for this class of problems can not be overtaken for the cargo scheduling problems in tramp shipping due to the special properties of maritime transportation including the fact that ships operate 24 hours a day and have special physical and legislative constraints. General surveys on ship routing and scheduling can be found in (Ronen, 1983 and Christiansen, Fagerholt, and Ronen, 2004). In (Ronen, 1983) one of the first detailed classification schemes for ship routing and scheduling problems is introduced. This paper presents also a first analysis of the differences between the vehicle and ship scheduling and routing problems. It includes almost all modes of shipping like short and long-term as well as liner, tramp and industrial shipping and further criteria that support the classification of the problem and the choice of the appropriate solution methods. The proposed classification schema focuses on the cost optimization and includes only port entry constraints for the ship and no further ship design or stability constraints. Same holds for the classification schema presented in later papers as for example (Christiansen, Fagerholt, and Ronen, 2004). One of the latest general survey papers is (Christiansen, Fagerholt, Nygreen, et al., 2013). (Appelgren, 1969) and (Appelgren, 1971) are two of the first papers dealing with the problem of the optimal assignment of cargoes to a given fleet under consideration of all tramp shipping specific requirements. In both papers the author presents a mixed integer linear program formulation of the scheduling problem and uses Dantzig-Wolfe decomposition and branch and bound to solve small instances of the problem. In the following years the formulation of the cargo routing and scheduling problem has evolved by including more parameters and making the models more realistic as it is being stated in (H.S. Hwang, Vi- soldilokpun, and Rosenberger, 2008). Varying the ship's speed and using it as a decision variable (Norstad, Fagerholt, and Laporte, 2011) has lead to significant changes in the results and cost saving (Fagerholt et al., 2013). On the other side the introduction of this variable has increased the complexity of the MILPs as well as the solution time. Beside this sailing much slower than service speed may look good in theory but often forces the ship to put the helm at big angles which causes a major increase in resistance and thus implifying an increase in operational cost and risk of casualty. For solving large and real world data instances different problem specific heuristic methods like the ones proposed in (Malliappi, Bennell, and Potts, 2011 and Jetlund and Karimi, 2004) as well as known local search methods including tabu search, as presented in (Korsvik, Fagerholt, and

Laporte, 2010), have been developed. A further parameter being considered in later works as in (Brønmo et al., 2007) is the parcel size, which in most cases is considered as fixed. In this work a genetic algorithm that takes advantage of the problem's specific structure and properties is implemented and enables the solution of large data instances within reasonable computation time. In (Cóccola and Méndez, 2015) a combination of a small instance MILP and a heuristic that delivers near-optimal solutions for large-scale cargo scheduling problems is presented. The focus of the mathematical model lies in costs minimization and the constraints do not include any ship design requirements from a stability point of view. The benchmark paper (Hemmati et al., 2016) gives a state of the art overview of the formulations for cargo routing and scheduling problems and proposes a benchmark suite for different real world size problems. It is one of the first papers dealing with the lack of standardized data for scheduling problems in tramp shipping and proposing data for benchmarks. In this paper a modern implementation of the adaptive large neighbourhood search (ALNS) heuristic method is presented which has been developed firstly by (Ropke and Pisinger, 2006). One of the latest papers (Homsi et al., 2018) presents a branch and price algorithm as an exact method and a hybrid metaheuristic for large instances considering 50 ships and 130 cargoes. To our knowledge, in actual existing formulations and proposed solution methods for the cargo scheduling problem in tramp shipping none of them are really considering the stability or the design of the ships as an integral constraint of the MILP. In (Fagerholt et al., 2013) the stability of ships that transport very special cargo is mentioned as a constraint to be taken into consideration. It is checked manually by the engineering department which can revoke the solution if the ship is not stable with the given load.

3 Problem Description and Formulation

The main purpose of this paper is to present a MILP formulation of the cargo scheduling problem in tramp shipping under consideration of ships stability constraints. The problem considers long-term orders to be charged and discharged in different ports within a given time frame. Each order has its own profit value. The fleet of tankers is homogeneous and each ship has a different design and number of cargo tanks. Compatibility constraints for different cargo types are taken into account. For safety reasons not all chemicals can be charged to adjacent tanks as well as in succession in the same tank. These requirements are formulated as constraints in the MILP. Cargo can also be charged and discharged between ships. In maritime terms, this is called ship-to-ship operation. The velocity of the ships is assumed to be constant.

The assignment of cargo to a ship from the fleet is checked for intact stability based on the ships design, its cargo hold configuration and the filling level of each tank. The rules from (IMO, 2002) that apply to tankers are checked by taking free surfaces of the liquid cargo into account. This means that the solution of the MILP solver could assign only partially filled tanks what represents common practice in tanker operation. Because the free surface of a fluid within any tank aboard causes huge reduction of the stability of the ship the model for stability calculation has to be precise. The gain one obtains is a much greater set of possible solutions for the fleet optimisation problem.

The objective function of the problem consist of finding the most profitable assignment of cargoes to the ship tanks compliant with the ships stability requirements and time constraints of the orders. The interplay between the stability checker and the MILP leads to reduction of the feasible region. Nevertheless the problem is very hard to solve and even small data instances take a very long time to achieve an optimal solution with a zero gap. In this section the problem formulation as a MILP and the stability calculations are presented in detail.

3.1 Integer Program

The aim of this integer program is to determine the fleet coordination while maximizing the number of fulfilled orders and while minimizing the costs, which arise from loading and unloading cargo in ports and from the ship travelling from one port to another.

Parameters

λ_{spq}	The cost per journey of a ship s from port p to q.
μ_{sp}	The cost per loading process of ship s in port p.
P	The set of all ports.
S	The set of all ships.
T	The time horizon.
Y	The set of all types of goods.
C	The set of all tanks.
O	The set of all orders.
c_{size}	The size of tank c.
s_{size}	The size of ship s.
τ	The loading time, i.e. how long a ship has to be in a port to finish the loading (same for all ships)
C_s	The set of all tanks on ship s.
γ_{zy}	is one, if good $y \in Y$ cannot be carried next to good $z \in Y$ on a ship, otherwise zero.

A_c	The set of all tanks, which are adjacent to tank c.
δ_{zy}	is 1, if good y can be carried immediately after good z in a tank.
PB_o	The pickup begin of order o. Similar for PE (pickup end), DB (delivery begin) and DE (delivery end).
$amount_o$	The amount of the good, which is ordered in order o.
r_o	The amount of money which is earned when fulfilling order o.
$type_o$	The type of good which is ordered in order o.
α_{spq}	The time it takes ship s to travel from p to q.
s_c	is the ship s which carries tank c.
C_L^S	the set of all tanks on ship s which have some sort of loading in a given solution.

Variables

p_{spt}	is 1 if ship s is at port p at time t.
ℓ_{spt}	is 1 if ship s is at port p at time t and just finished loading.
a_{spqt}	is 1 if ship s just ended a cruise from port p to port q at t.
h_{cyt}	is the amount of type y tank c contains at time t.
b_{cyt}	is 1 if tank c contains at least 1 unit of type y at time t.
x_{cyat}	is 1 if tank c contains exactly the amount a of type y at t.
f_{sypt}	is the amount of type y which flows from ship s to port p at t.
g_{ot}	the amount of order o to be picked up at time t.
d_{ot}	the amount of order o delivered at time t.
e_o	is one if and only if order o is completed.

The following function represents the objective function to be used in the problem setting. It contains two terms that represent the earning maximization and the port as well as journey cost minimization leading in total to a profit maximization.

$$\max \sum_{o \in O} e_o \cdot r_o - \left(\sum_{s \in S} \sum_{p \in P} \sum_{t \in T} \left(\mu_{sp} \cdot \ell_{spt} + \sum_{q \in P} \lambda_{spq} \cdot a_{spqt} \right) \right) \qquad (*)$$

Constraints

$$\begin{gathered} 0 \leq p_{spt} \leq 1 \; \forall s \in S, p \in P, t \in T \\ 0 \leq \ell_{spt} \leq 1 \; \forall s \in S, p \in P, t \in T \\ 0 \leq a_{spqt} \leq 1 \; \forall s \in S, p, q \in P, t \in T \\ 0 \leq h_{cyt} \leq c_{\text{size}} \; \forall c \in C, y \in Y, t \in T \\ 0 \leq b_{cyt} \leq 1 \; \forall c \in C, y \in Y, t \in T \\ 0 \leq x_{cyat} \leq 1 \; \forall c \in C, y \in Y, t \in T, 0 \leq a \leq c_{\text{size}} \\ -s_{\text{size}} \leq f_{sypt} \leq s_{\text{size}} \forall s \in S, \forall y \in Y, \forall p \in P, \forall t \in T \\ 0 \leq g_{ot} \; \forall o \in O, t \in T \\ 0 \leq d_{ot} \; \forall o \in O, t \in T \\ 0 \leq e_o \leq 1 \; \forall o \in O \end{gathered} \qquad (1)$$

The constraints in equation 1 set the basic domains of the variables.

$$\sum_{p \in P} p_{spt} \leq 1 \forall s \in S, t \in T \qquad (2)$$

Constraint 2 ensures that a ship s is at no more than one port at a time.

$$\ell_{spt} = 0 \qquad \forall s \in S, p \in P, t < \tau, t \in T \qquad (3)$$

Constraint 3 ensures that in the beginning no ship finishes loading before it was in the port for at least τ time slots.

$$\sum_{u=t-\tau}^{t} p_{spu} \geq (\tau+1)\ell_{spt} \qquad \forall s \in S, p \in P, t \geq \tau \quad (4)$$

Constraint 4 ensures that the ship was in port p for at least τ time slots before it finishes loading. Note that ℓ_{spt} doesn't have to be equal to one if the ship was at the port for τ time slots.

$$\sum_{p \neq q \in P} a_{spqt} \geq p_{sqt} - p_{sq(t-1)} \; \forall s \in S, q \in P, t \geq 1 \qquad (5)$$

Constraint 5 ensures that if a ship s is in port q in time t, it either was in port q at time $t-1$ or it just arrived, i.e. ended a cruise from port p to q for some p.

$$a_{spqt} = 0 \quad \forall s \in S, p \neq q \in P, t < \alpha_{spq} \qquad (6)$$

where α_{spq} is the distance between p and q divided by the speed of ship s. Constraint 6 sets all variables α_{spq} equal to zero, if there is no possibility, that a ship arrived from p at q at time t.

$$p_{sp(t-\alpha_{spq})} - \alpha_{spq} a_{spqt} + \alpha_{spq} - 1 \quad \geq \sum_{r \in P} \sum_{u=t-\alpha_{spq}+1}^{t-1} p_{sru}$$

$$\forall s \in S, p \neq q \in \mathrm{P}, t \geq \alpha_{spq} \qquad (7)$$

If α_{spq} equals zero, constraint 7 has no impact since the left hand side is greater or equal to $\alpha_{spq} - 1$ and the right hand side is at most $\alpha_{spq} - 1$ because of constraint 2. If α_{spqt} = 1 (which means ship s just arrived from a cruise from p to q), ship s must have been in port p at time

$t - \alpha_{spq}(p_{sp(t-\alpha_{spq})} = 1)$, because otherwise the left hand side would be equal to minus one and the right hand side is not negative. So in this case the left hand side is equal to zero and therefore the ship couldn't be somewhere else other than on the cruise from p to q in the mean time, which means each p_{sru} on the right hand side has to be equal to zero.

$$h_{cyt} \leq c_{\text{size}} \cdot b_{cyt} \quad \forall c \in C, y \in Y, t \in T \tag{8}$$

Constraint 8 ensures that the variable b_{cyt} is set to one if tank c is loaded with some cargo type y at time t.

$$\sum_{y \in Y} b_{cyt} \leq 1 \quad \forall c \in C, t \in T \tag{9}$$

Constraint 9 ensures that a tank carries just one type of good at a time.

$$\sum_{c \in C_s} \left(h_{cyt} - h_{cy(t-1)}\right) + \sum_{p \in P} f_{sypt} = 0 \qquad \forall s \in S, y \in Y, t \geq 1 \tag{10}$$

Constraint 10 ensures that the change in the amount of good of type y on ship s from t to $t - 1$ equals the flow of good y from ship s to some port at time t.

$$\left|f_{sypt}\right| \leq s_{\text{size}} \cdot \ell_{spt} \qquad \forall s \in S, p \in P, t \in T, y \in Y \tag{11}$$

Constraint 11 ensures that the flow f_{sypt} of type y from the ship s to port p is at most the size of the ship at each time.

$$\left|h_{cyt} - h_{cy(t-1)}\right| \leq c_{\text{size}} \cdot \sum_{p \in P} \ell_{s_c pt} \qquad \forall c \in C, y \in Y, t \geq 1 \tag{12}$$

where s_c denotes the ship s which carries tank c. This constraint 12 ensures that the amount of a good y in a tank just changes if the ship is at least τ time slots in a port to finish loading and that the change in the amount of y in c from $t-1$ to t is at most the size of this tank.

$$\sum_{s \in S} f_{sypt} + \sum_{\substack{o:from_o = p \\ \wedge y_o = y}} \left(g_{o(t-1)} - g_{ot}\right) = \sum_{\substack{o:to_o = p \\ \wedge y_o = y}} \left(d_{ot} - d_{o(t-1)}\right)$$

$$\forall p \in P, y \in Y, t \geq 1 \quad (13)$$

Constraint 13 ensures that the flow of good y from all ships into the port at each time t plus the change in the amount of y which is to be picked up (i.e. the flow of good y from the port onto the ship) equals the change in the amount of y which is to be delivered. Note that f_{sypt} can be negative, i.e. a flow from the port onto a ship.

$$d_{ot} \geq d_{o(t-1)} \quad \forall o \in O, t \in T \quad (14)$$

$$g_{ot} \leq g_{o(t-1)} \quad \forall o \in O, t \in T \quad (15)$$

Constraints 14 and 15 ensure that the amount of a delivered good y within an order just increases and similar the amount of a good y to be picked up within an order just decreases. The binary variables x_{cyat} are introduced solely for the reason to exclude a specific loading configuration of a ship. With the following two constraints we set x_{cyat} equal to 1 if and only if exactly the amount $a > 0$ of type y is in tank c at time t:

$$\sum_{a=1}^{c_{\text{size}}} x_{cyat} = b_{cyt} \qquad \forall c \in C, y \in Y, t \in T \quad (16)$$

$$\sum_{a=1}^{c_{\text{size}}} a x_{cyat} = h_{cyt} \quad \forall c \in C, y \in Y, t \in T \tag{17}$$

With these variables we are able to tell the program to forbid a specific loading configuration if the ship stability constraints are hurt. Assume we have a solution which is feasible for our program, but does not satisfy the stability constraints. Let s be the ship which is instable when leaving port p. Our aim is to forbid exactly the given loading configuration for ship s. C_L^s is the set of all tanks on ship s which have some sort of loading in our solution. Let y_c be the type which is loaded in $c \in C_L^s$ and similar a_c the amount of type y_c in c. From constraints 16 and 17 we know that $x_{cyat} = 1$ for $y = y_c$ and $a = a_c$ and zero otherwise. We then are able to add a constraint which ensures that the loading configuration for ship s is changed:

$$\sum_{c \in C_L^s} \left(1 - x_{c y_c a_c t}\right) + \sum_{c \in \left(C_s \setminus C_L^s\right)} \sum_{y \in Y} h_{cyt} \geq p_{sp(t-1)} - p_{spt} \quad \forall t \in T \tag{18}$$

The right hand side of constraint 18 just defines the time slot t at which the ship s leaves port p, since for t the right hand side equals 1 and for all other time slots it is at most zero. The left hand side is zero for our given solution with which ship s is instable. To change the loading configuration we have two options. Either we change the amount of the loading in our tanks $c \in C_L^s$ so that in the first sum of the left hand side we get that at least one $x_{c y_c a_c t}$ is zero. Or additional tanks are loaded so that in the second sum at least one h_{cyt} gets at least one.

Another problem we need to address is the specific adjacencies of tanks on the ship. There are goods which are not allowed to be carried next to each other on a ship for various safety reasons. Therefore our feasible solution has to ensure that these adjacencies are considered. This adjacency constraint is constructed via the parameter γ_{xy}:

$$b_{cyt} \leq 1 - \sum_{\tilde{c} \in A_c} \sum_{\tilde{y} \in Y} \gamma_{\tilde{y}y} b_{\tilde{c}\tilde{y}t} \quad \forall c \in C, y \in Y, t \in T \tag{19}$$

The right hand side of constraint 19 is less or equal zero if and only if there is a tank adjacent to c, which is loaded with a good $\tilde{y}$ that is not allowed to be carried next to good y. Therefore b_{cyt} has to be equal zero, which means that tank c is not allowed to load good y at time t.
Similarly there are goods which are not allowed to be carried in a tank directly after another good, because for example there have to be two separate cleanings between carrying those two goods.

$$b_{cyt} \leq 1 + \sum_{\tilde{y} \in Y} \left(\delta_{\tilde{y}y} - 1\right) b_{c\tilde{y}(t-1)} \forall c \in C, y \in Y, \geq 1 \tag{20}$$

The right hand side of constraint 20 equals one if and only if either the tank c didn't carry any good at time $t-1$ or good y is allowed to be carried immediately after the good which was in the tank at $t-1$. Otherwise the right hand side equals zero and therefore b_{cyt} has to be zero, meaning good y is not allowed to be in tank c at time t.
The following constraints set the variable e_o to one if and only if order o is completed, which is important for our objective function:

$$\begin{gathered} g_{oPE_{\mathrm{o}}} = 0 \ \forall o \in O \\ d_{o(DB_{\mathrm{o}}+\tau-1)} = 0 \ \forall o \in O \\ d_{oDE_{\mathrm{o}}} = amount_{\mathrm{o}} \cdot e_o \ \forall o \in O \\ g_{o(PB_{\mathrm{o}}+\tau-1)} = amount_{\mathrm{o}} \cdot e_o \ \forall o \in O \\ g_{o0} = amount_{\mathrm{o}} \cdot e_o \ \forall o \in O \end{gathered} \tag{21}$$

For the sake of running time we constructed a few extra constraints, which are direct consequences of the constraints presented above, but help the program to exclude infeasible solutions faster.

$$\tau\left(p_{spt} - p_{sp(t-1)}\right) \leq \sum_{i=1}^{\tau} p_{sp(t+i)} \; \forall s \in S, p \in P, t \geq 1 \quad (22)$$

The statement of constraint 22 is, that if a ship arrived at a port, it stays at this port for at least the τ time slots it takes to (un)load. This ensures that a ship doesn't go to a port without doing anything there.

$$\sum_{t=1}^{T} \sum_{p \in P} f_{sypt} = 0 \quad \forall s \in S, y \in Y \quad (23)$$

Constraint 23 is a consequence from the fact that a ship is empty in the beginning and in the end, so the sum of the flow from each ship to all ports equals zero for each good over the time span.

$$\sum_{y \in Y} max\{0, \sum_{\substack{o:\mathrm{PB_o} \geq a_i \\ \wedge \mathrm{PE_o} \leq u_j \\ \wedge \mathrm{type_o} = y}} amount_{\mathrm{o}} - \sum_{\substack{o:\mathrm{DB_o} \leq u_j \\ \wedge \mathrm{DE_o} \geq a_i \\ \wedge \mathrm{type_o} = y}} amount_{\mathrm{o}}\} \leq \sum_{t \in [a_i, u_j]} \sum_{s \in S} s_{\mathrm{size}} \ell_{spt}$$

$$\forall p \in P, a_i, u_j \in T, a_i \leq u_j \quad (24)$$

Constraint 24 ensures that for each time interval at a port the sum of the sizes of ships that load in this port are large enough, meaning the sizes of the ships are able to fit all orders.

3.2 Ship stability calculation

In general the stability of a ship is the ability to come back to a stable equilibrium after any perturbation caused the ship to heel or trim. Because usually the trim does not cause safety issues this is not a matter of safety. To make sure that all ships on duty do withstand such influences there are certain rules that apply to the ship. These rules are issued by the *International Maritime Organisation* (IMO) and apply to any ship of more than 24 m length. Before a ship will leave the harbour, the master shall ensure that the ship is compliant to these rules for the current loading condition as well as for the condition when arriving at the destination. Accidents due to lack of stability lead to cost and reputation loss which has a great impact in company's future contracts and therefore a long-term effect.

Even though the stability of a tanker ship might not be a major issue in the first place, in particular because bulk carriers for any kind are well known for their high stability, it is necessary to check whether a ship does fulfill the stability criteria from the IMO, 2002 (2008 IS-Code) or it will not be allowed to leave the harbour. Because the *MILP* solver does not know if a ship would be capable of sailing at a given loading condition the stability has to be taken into account when choosing an admissible solution for the fleet scheduling problem.

Therefore the results of the *MILP* solver, where its output is the loading condition of each ship of a fleet at departure, have to be evaluated. A separate program has been written to perform stability calculations when it has been given a ship and its loading condition as input. The output of the program is a boolean *true/false* that indicates the stability of the loaded ship. As shown below this is an admissible way to involve the requirements evaluation because of the interlaced quantities and the non linearity of the problem. There is no way of formulating the ship stability problem in terms of linear inequalities.

Because a ship always has the ability of using ballast water to become stable enough, this has to be taken into account. Therefore the model contains ballast water tanks and every possible combination of full and empty ballast water tanks is tested until stable conditions are reached. If this was successful the program returns *true* to mark that the ship is compliant. If all combinations are checked but the rules are not fulfilled for any of the ballast water tank combinations, the program returns *false* to mark that the ship is not be compliant. All rules described in the following subsection are well known and only a brief introduction shall be given here.

3.3 General aspects of ship stability

In ship building the following approach to perform the stability evaluation is required and commonly used. The 2008 IS-Code asks for certain properties of the lever arm curve ($\overline{\mathrm{GZ}}$ curve) that have to be fulfilled at any situation at sea. The $\overline{\mathrm{GZ}}$ curve is defined as the distance between the alignment of the vector of the gravity force G and the vector of the buoyancy force B. The $\overline{\mathrm{GZ}}$ curve of one of the example ships used for the numerical experiments described in section 4 is shown in Figure 2. While the ship is upright we have $\overline{\mathrm{GZ}} = 0$. As soon as the ship heels, B moves towards the side of the ship. Close to the favourable stable equilibrium the forces cause a torque that pushes the ship back into the upright position. For a more detailed description see e.g. (Biran, 2003 and Tupper, 2013).

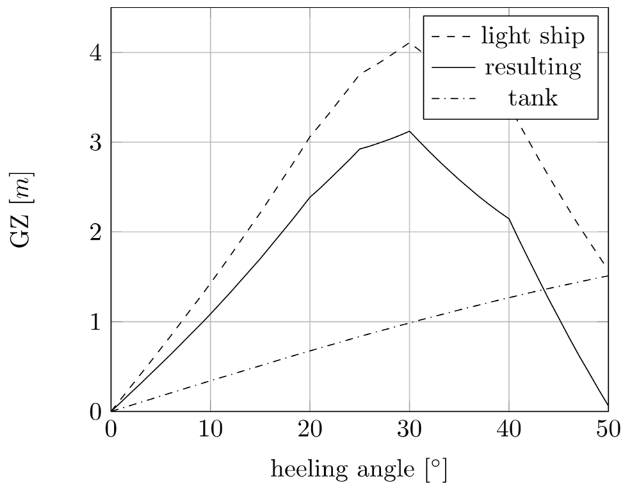

Figure 2: $\overline{\mathrm{GZ}}$ curve of one of the example ships

In general, the gravity force G and buoyancy force B have to be at an equilibrium when the ship does not move, viz. $\mathrm{B} = \mathrm{G}$, which is obvious due to the principle of linear momentum. The principle of angular momentum leads to the fact that the righting and the heeling lever arm have to be equal at an equilibrium. Therefore, it is common practice to only look at the lever arms for evaluating the ships hydrostatics. $\overline{\mathrm{GZ}}$ depends on the heeling angle and on the displacement of the ship. Because the lever arm is always calculated for one particular displacement this dependency is neglected in the following. The righting lever arm $\overline{\mathrm{GZ}}_{\mathrm{LS}}$ (the dashed line in Figure 2) for the light ship is defined by

$$\overline{\mathrm{GZ}}_{\mathrm{LS}}(\varphi) = \overline{\mathrm{KN}}(\varphi) - \overline{\mathrm{TCG}}_{\mathrm{LS}}\cos(\varphi) - \overline{\mathrm{VCG}}_{\mathrm{LS}}\sin(\varphi) \quad (25)$$

where $\overline{\mathrm{TCG}}_{\mathrm{LS}}$ is the transverse and $\overline{\mathrm{VCG}}_{\mathrm{LS}}$ the vertical distance of the center of gravity of the light ship to the keel and

$$\overline{\mathrm{KN}}(\varphi) := \overline{\mathrm{TCB}}(\varphi)\cos(\varphi) + \overline{\mathrm{VCB}}(\varphi)\sin(\varphi) \tag{26}$$

with the transverse distance $\overline{\mathrm{TCB}}$ and the vertical distance $\overline{\mathrm{VCB}}$ of the center of buoyancy in global coordinates. $\overline{\mathrm{KN}}$ is also known as the cross curves of stability when evaluated for different displacements. In Figure 3 this is illustrated. There the center of gravity, marked as CG_0 and CG_ϕ, as well as the center of buoyancy, marked as GB_0 and CB_ϕ, are shown. The index stands for either no heeling angle ($\varphi = 0°$) or at some heeling angle ($\varphi > 0°$).

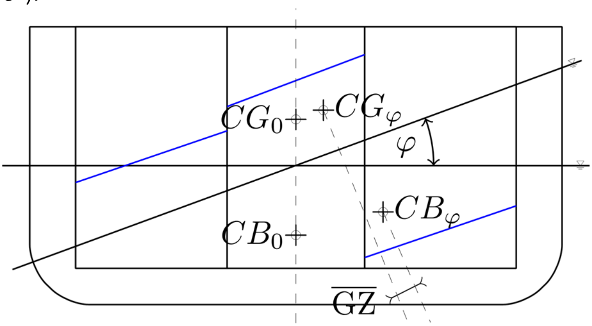

Figure 3: Midship section

The position of the center of gravity of the ship has to be calculated according to the loading status of the ship by:

$$\overline{\mathrm{TCG}}(\varphi) = \overline{\mathrm{TCG}}_{\mathrm{LS}} \frac{\Delta_{\mathrm{LS}}}{\Delta} + \frac{1}{\Delta} \sum_{l=1}^{n_l} y_{G,l}(\varphi) V_l \rho_l \tag{27}$$

$$\overline{\mathrm{VCG}} = \overline{\mathrm{VCG}}_{\mathrm{LS}} \frac{\Delta_{\mathrm{LS}}}{\Delta} + \frac{1}{\Delta} \sum_{l=1}^{n_l} z_{G,l}(\varphi) V_l \rho_l \tag{28}$$

where $y_{G,l}(\phi)$, $z_{G,l}(\phi)$ are the transverse and vertical position of the center of gravity of each single cargo hold, bunker and stores compartment and ballast water tank. In the case of a free surface the position of the center of gravity of the fluid within the tank changes due to the heeling angle of the ship.

The effective righting lever arm $\overline{\mathrm{GZ}}_{\mathrm{eff}}$, which is the $\overline{\mathrm{GZ}}_{\mathrm{LS}}$ of the light ship corrected by the tank lever, as shown in Figure 2 (dashed/dotted line), is calculated by

$$\overline{\mathrm{GZ}}(\varphi) = \overline{\mathrm{KN}}(\varphi) - \overline{\mathrm{TCG}}(\varphi)\cos(\varphi) - \overline{\mathrm{VCG}}(\varphi)\sin(\varphi) \tag{29}$$

which leads to the continuous curve in Figure 2. Thus the difference between the lever arm of the light ship (dashed line in Figure 2) at the draught matching the displacement the ship in loaded condition and the effective lever arm is a reduction caused by the cargo and in particular because of the free surface. This effect is described in detail in e.g (Biran, 2003 and Tupper, 2013).

3.4 Criteria for intact stability

The criteria which the 2008 IS-Code demand can be written as

$$\int_{0^\circ}^{30^\circ} \overline{\mathrm{GZ}}_{\mathrm{eff}}(\varphi)\mathrm{d}\varphi \geq 0.055\mathrm{mrad} \tag{30}$$

$$\int_{0^\circ}^{40^\circ} \overline{\mathrm{GZ}}_{\mathrm{eff}}(\varphi)\mathrm{d}\varphi \geq 0.09\mathrm{mrad} \tag{31}$$

$$\int_{30^\circ}^{40^\circ} \overline{\mathrm{GZ}}_{\mathrm{eff}}(\varphi)\mathrm{d}\varphi \geq 0.033\mathrm{mrad} \tag{32}$$

$$\overline{\mathrm{GZ}}_{\mathrm{eff}}(\varphi^*) := \max \overline{\mathrm{GZ}}(\varphi) \text{ with } \varphi^* \leq 25^\circ \tag{33}$$

$$\overline{\mathrm{GZ}}(\varphi \geq 20^\circ) \geq 0.3\mathrm{m} \tag{34}$$

$$\overline{\mathrm{GM}}_0 \geq 0.15\mathrm{m} \tag{35}$$

where $\overline{\mathrm{GM}}_0$ is the metacentric height of the upright floating ship. The criteria 30 to 35 aim at ensuring a certain amount of energy a ship is able to take up without risking to capsize. In addition to the mentioned criteria the weather criterion has to be fulfilled. The basic idea is, that at the worst situation at sea a seafarer may think of, in terms of intact stability of the ship, the ship shall withstand without being at risk of capsizing. For detail see (Meier-Peter, 2012).

3.5 Application

In the program the above described criteria are implemented and evaluated for the *MOERI Tanker KVLCC2* which is widely known in research. The cross curves of stability as well as the displacements and other parameters are provided in tabular form for heeling angles from 0° to 50° and displacements from $141,000t$ to approximately $321,000t$. The values at an intermediate state are interpolated linearly to avoid overestimation of the capability of the ship. For reasons of simplification the free surface of fuel oil tanks and fresh water tanks is not taken into account. These tanks are small compared to the ships size and do not have an impact on the ships stability that is worth mentioning. But the free surfaces of a cargo hold that is not fully filled or empty shall be taken into account. Therefore a simplified tank model is chosen to determine the center of gravity when the ship heels (see Figure 3). A quadrilateral shape of the transverse section is assumed. This allows an analytical solution for the tank lever arms depending on the heeling angle and the filling height of the tank. The integration of the resulting $\overline{\mathrm{GZ}}_{\mathrm{eff}}$ is realised by a simple quadrature and the interpolation. The criteria may also be fulfilled not only at the departure condition but also at the arrival condition to ensure that at every intermediate state reached during the journey no unsafe condition occurred.

1. departure conditions with 100 % bunkers and stores
2. arrival conditions with 10 % bunkers and stores

The loading condition of each cargo hold of a ship within the fleet is set as a result of the MILP. Then the criteria described above are checked for each ship and a boolean true is returned if and only if all criteria at departure and arrival are fulfilled.

4 Experiments and Analysis

As real world data was not available to us, we produced some artificial instances. Due to the complexity of the problem and its exponential growth we could only test the model on small instances. This means there is a small number of orders and ports as well as a quite short time interval for few ships that made the input parameters.

Table 1: Instance data

#	ships	ports	orders	time steps
1	2	3	6	15
2	3	4	110	30
3	3	3	7	15
4	3	3	7	15
5	3	3	7	15

The MILP program is implemented in C++ and the GUROBI (8.1) solver (academical license) is used for solving the problem. We ran the solver on a quad-core processor (i5-6600 CPU @ 3.30GHz) with 16 GB random access memory. The stability calculations are also implemented in C++ and communicate directly with the MILP. Whenever a MILP solution is found, it is passed to a function that returns **true** or **false** depending on whether the stability constraints are satisfied.

All ships in all five problems are of the same type. They have 15 tanks with a volume of approximately $10,000$ litres or $15,000$ litres. They are arranged in a 3 X 5 grid, which is important for both the ship stability constraints as well as the adjacency constraints. The tank volumes were discretized into units of volume $5,000$ litres to reduce computation time.

Instance 1 was constructed to have a feasible solution with respect to the ship stability constraints. It was solved in 5 seconds. The optimal solution completed all orders.

Instance 2 turned out to be much harder to solve than the first one. After 20 minutes the solver found a solution, which completes 7 out of 10 orders.

After two hours in total, we stopped the program. It had not found a better solution in the meantime. The MIP gap was at 44%.
Instance 3 to 5 were the same with minor differences. Compared to instance 3, in instance 4 we set $\gamma_{z,y} = 0$ and $\delta_{z,y} = 1$ to remove all good type restrictions. Instance 5 in turn was the same as instance 3 except that we multiplied all densities of good types by 0.7, which relaxes the ship stability constraints. The lighter the goods, the smaller is the effect on the stability. During the two hours in which we let the solver tackle this problem, its best solution was found already after about half an hour. In the remaining time the solver was able to reduce the MIP gap to 17.7%. Removing the good type restrictions did not help the solver find a solution. In fact, because it increased the number of solutions, it only found its best solution after 36 minutes. The gap after two hours was again 17.7%. Finally, for instance 5 the changes we made significantly affected the solver. The solution that was also found for instances 3 and 4 was already found after 5 minutes. Half an hour later it found a slightly better solution with respect to the number of journeys and loading operations. After a total of two hours it had decreased the MIP gap to 17.5%.

Table 2: Results with stability

#	obj. value * of best solution	time (s)
1	589	5
2	681	1113
3	587	1899
4	587	2199
5	588	1992

Table 3: Results without stability

#	obj. value * of best solution	time (s)	Intermediate result
1	589	5	
2	981	92	683 after 38 s
3	684	213	588 after 19 s
4	686	108	589 after 7 s
5	684	213	588 after 19 s

As a comparison we also ran the solver on these instances without stability constraints, which show significant differences in run time and in the best solution found within two hours. The objective values can be interpreted as follows: Each completed order adds 100 to the value and each loading operation and ship cruise subtracts 1 from it, i.e. we set $O_r = 100$, $\mu_{sp} = 1$ and $\lambda_{spq} = 1$.

As shown in Table 3 and 4, adding the stability constraints significantly influences the run time of the program. Instance 1 was solved in both cases very fast. But as soon as the tested instance got more complicated, the stability constraints led to a big difference in the run time. This can be explained by the number of solutions of the MIP which have to be tested in order to find a feasible solution for the stability constraints. In the case that the progam finds a feasible solution with objective value k, it has to test whether this solution satisfies the stability constraints. If not, the program tries to find a different assignment to achieve an objective value k. If the stability constraints are excluded, the program directly tries to improve the objective value, which means that significantly fewer feasible solutions for the MIP have to be found. This also explains why the best solution with stability constraints takes way longer to find than to find a solution with this objective value without stability constraints. Unfortunately real world problems are much larger than our test instances. To conduct more meaningful numerical experiments, we need to further develop our approaches.

5 Conclusions and Future Work

This work shows that mathematical models and methods can improve the planning process significantly and give well-founded decision support for planners. With this first model it has been shown that the integration of non linear requirements as the ship stability check to common MILP formulations of the cargo scheduling problems is possible. This inclusion makes the model even more realistic and enables calculations of scenarios that are very time consuming done in a manual way. The constraints of this MILP formulation link many different aspects of the cargo scheduling problem making it on the one side quite complex to solve real-world instances exactly and more realistic on the other side. This formulation is a first draft and further analysis of the numerical results need to be made in order to identify performance potentials. The examination of appropriate algorithms and methods, that take advantage of special problem structure and properties, is missing and is considered to be one of the main factors with a big impact in the calculation time. The development of appropriate heuristics is also one key aspect to be taken into consideration for future work. Beside the performance issue the model itself can be made even more realistic by considering the speed as a decision variable and fuel consumption in dependence to loading. From a ship design point of view, in particular for bulk carriers of liquid or solid cargo, the longitudinal strength is a problem worth mentioning. In this work the view on mechanical requirements is neglected but for real world application an evaluation also has to be applied to the algorithm. Modeling the complex problem of cargo scheduling as realistically as possible and adapting methods for solving real data instances is one of the main future challenges.

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